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# Exploring variations and temporal instability of factors affecting driver injury severities between different vehicle impact locations under adverse road surface conditions

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## Abstract

The adverse road surface condition has been identified as an important factor resulting in serious casualties and property losses in traffic accidents, and there is a tremendous need to uncover the interaction mechanism between deteriorating road surfaces and vehicle impact locations on the driver injury severity at a disaggregate level. In this paper, three groups of random parameters logit models with heterogeneity in means (and variances) are developed to investigate the unobserved heterogeneity and temporal stability of the determinants affecting driver injury severity outcomes across different damage locations among single-vehicle crashes that occurred under adverse weather conditions. A three-year crash dataset gathered from January 1, 2015, to December 31, 2017, in Ohio is utilized. Three crash injury severity categories including no injury, minor injury, and severe injury are identified as outcome variables, while crash characteristics, driver characteristics, temporal characteristics, vehicle characteristics, roadway characteristics, and environment characteristics are regarded as potential predictors influencing driver injury severities. Additionally, likelihood ratio tests and marginal effects are used to assess the temporal instability and impact location non-transferability of the explanatory variables. The results indicate an overall temporal and locational instability of model estimates while several determinants are identified to have consistent effects on injury severity outcomes such as animal-involved collisions, old drivers, safety restraint usage, female drivers, physically impaired drivers, and vehicles with insurance. This study also quantifies and characterizes the net effect of year-to-year and location-to-location shifts through probability differences between out-of-sample predictions and within-sample observations. Varying magnitudes and inconsistent directions of distribution characteristics (mean, skewness, kurtosis, and prediction accuracy) in the probability differences across different impact locations over time are captured. Moreover, this study indicates that the non-transferability of collision locations has a greater impact on the prediction accuracy than the temporal instability. The findings could potentially serve as a reference for transportation administrators to formulate effective safety strategies to better protect drivers from adverse-road-related crashes.

**Keywords:** Adverse-road-related crashes; Vehicle impact locations; Random parameters logit model; Unobserved heterogeneity; Temporal instability; Out-of-sample prediction.

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## 1. Introduction

The adverse road surface condition has been widely acknowledged as a vital determinant that has a remarkable impact on the likelihood of accident occurrences and injury severities. Accompanied by deteriorating driving conditions such as decreased visibility, irregular yaw rate feedback, and poor emergency braking performance (Koylu and Tural, 2021), driving in unfavorable road circumstances could dramatically increase the frequency of driving errors and dangerous driving behaviors (Alnawmasi and Mannering, 2019; Yan et al., 2021a). According to the Federal Highway Administration (FHWA, 2022), there is approximately 75% of automobile accidents occurred on wet pavements every year in the United States. Specifically, almost 5,700 people are killed and over 544,700 are wounded in these crashes. Meanwhile, snowy, slushy, and icy pavements account for 24% of all weather-related vehicle collisions each year, with over 1,300 people being killed and over 116,800 people being injured. Note that other than serious safety issues, adverse road surfaces could also cause traffic delays and inflict damage to roadway infrastructure (FHWA, 2022). In this context, special emphasis should be given to uncover the underlying mechanism of how related factors affect the driver injury severity outcomes in adverse-road-related crashes, which has the potential to improve road safety and minimize associated expenditures.

Numerous empirical studies have been conducted to disentangle the impact of adverse road surface conditions on the crash injury severity (Abohassan et al., 2021; Behnood and Mannering, 2019; Fountas et al., 2020; Hou and Chen, 2020; Islam and Mannering, 2020, 2021; Morgan and Mannering, 2011; Pang et al., 2022; Wang et al., 2018; Yan et al., 2021b). For instance, Islam and Mannering (2020) examined the variation of determinants in crash injury severities involving aggressive and non-aggressive driving behaviors. The analysis revealed that the wet surface indicator exhibited statistical significance with a higher likelihood of minor and severe injuries in non-aggressive driving crashes. Yan et al. (2021b) explored the spatiotemporal instability of driver injury severities in adverse weather conditions and discovered that the wet road surface indicator had positive marginal effects on severe injuries in the 2014 Ohio model due to the slippery pavement surface, while it was negatively associated with severe injuries in the 2013 Ohio model owing to the risk-compensating mechanism. Abohassan et al. (2021) employed the structural equation modeling method and path analysis to investigate the direct and indirect effects of weather variables and maintenance operations on pavement friction and collision occurrence during snowstorms. Their findings showed that icy road surfaces and wet slippery conditions had a detrimental impact on pavement friction and contributed to an increased risk of collisions. Nevertheless, only a limited number of studies have endeavored to disaggregate the adverse-road-related crashes at a specific individual level and explored the underlying mechanisms of how contributors determine the adverse-road-related driver injury severities. In the study conducted by Morgan and Mannering (2011), the mixed logit model was utilized to examine impacts of age and gender on the injury severity of single-vehicle crashes under different roadway surface conditions (dry, wet, and snow/ice-covered). The results indicated that female drivers and older male drivers exhibited an increased likelihood of severe injuries when crashes transpired on wet, snowy, or icy surfaces. Conversely, male drivers under 45 years old experienced a decreased probability of severe injuries under such conditions. Li et al. (2013) analyzed the correlation between several key pavement condition scores and injury severities based on crash records in Texas. The results indicated that there was a proportional association between poor pavement condition scores and more severe crashes, yet very poor pavement conditions were associated with less severe crashes. Chen et al. (2017) explored the unobserved heterogeneity and safety effects of pavement conditions on rural-road-related injury severities using the multivariate random parameters negative binomial specification. The results unveiled that the poor surface condition variable was identified as a significant random parameter with normal distribution in the crash model.

In addition to adverse roadway surfaces, the vehicle impact location could also have a considerable influence on the injury severity sustained by drivers as indicated in previous studies (Lai et al., 2012; Champahom et al., 2020; Yu et al., 2020; Liu and Fan, 2021; Wang et al., 2022). For example, Lai et al. (2012) conducted a statistical analysis to investigate the combined effects of specific impact directions and impact locations on serious-to-fatal injuries of driver occupants involved in near-side collisions, and the impact location was found to be a highly important crash characteristic. Li et al. (2014) found that the magnitude of lengthwise traffic variation between upstream and downstream locations was primarily related to the occurrence of rear-end collisions, while sideswipe collisions were associated with the type of freeway segment as well as crosswise traffic variation between adjacent lanes. Note that although Wang et al. (2022) investigated contributing factors of driver injury severities between rear-end and non-rear-end crashes, it is undeniable that drivers are more prone to sustaining severe injuries in near-side crashes than in far-side collisions due to the direct impact and significantly restricted survival space. Combining near-side and far-side collisions together may overlook the inhomogeneous injury outcomes and cause misinterpretations. However, to date, few studies have attempted to uncover the internal mechanism between deteriorating road surfaces and vehicle impact locations on the driver injury severity in single-vehicle crashes at a disaggregate level. Furthermore, the current knowledge regarding whether the determinants influencing adverse-road-related crash injury severities vary across different impact locations and the underlying mechanism behind such divergence is rather limited.

While extensive studies have been undertaken to understand the influence of adverse road conditions on driver injury severities, it cannot be ignored that they may not sufficiently accommodate the potential temporal instability and unobserved heterogeneity arising from various factors in adverse-road-related crashes, especially concerning individual vehicle impact location. Previous studies have witnessed contradicting findings and indicated that the effects of crash contributors on driver injury severities can vary over time in adverse-road-related crashes (Morgan and Mannering 2011; Mannering, 2018; Behnood and Mannering, 2019). Underestimating such temporal variations could potentially lead to improper recommendations for formulating road safety policies (Mannering, 2018). Additionally, the unobserved heterogeneity is also recognized as an essential element resulting in variations in driver injury severities among individual vehicle operators owing to different physical abilities, risk perceptions, and reactions to external stimuli (Mannering et al., 2016). Furthermore, it is important to acknowledge that while attempts are made to ensure the update and comprehensiveness of highway crash data, the collection of all pertinent information that could impact the occurrence of crashes is often limited by constraints related to costs and resources. For instance, collecting human factors such as distraction or the level of anxiety may pose considerable challenges in the case of highway single-vehicle crashes. This could inevitably introduce unobserved heterogeneity (Mannering, 2018). Failing to account for such heterogeneous mechanisms or treating existing variables as fixed can trigger model misspecification and biased parameter estimates (Alnawmasi and Mannering, 2019; Pervez et al., 2022), consequently resulting in inaccurate conclusions for effectively mitigating adverse-road-related crash injury severities across different impact locations. Nevertheless, to the best of the current knowledge, there are few studies attempting to investigate this aspect.

In this regard, it is crucial to investigate the variations in vehicle impact locations and temporal shifts of the factors that influence driver injury severities in the context of adverse road conditions while accounting for the unobserved heterogeneity. In addition to conventional likelihood ratio tests, recent studies have utilized the out-of-sample prediction to compare the group-to-group or year-to-year predictive differences (Hou et al., 2022; Xu et al., 2021). This approach aids in identifying shifts more accurately between different groups or periods and understanding the potential reasons underlying those shifts. For instance, Alnawmasi and Mannering (2022a) used out-of-sample simulations to examine the effects of increasing speed limits on the frequency and severity of crashes on freeways in Kansas. Results indicated that the aggregate impact of the changing influences of explanatory variables on average injury severities was relatively small. While the increased likelihood of rollover crashes in single-vehicle crashes implied that the higher speeds following the increase in the speed limit might have influenced the single-vehicle injury severity. In a recent study conducted by Alnawmasi and Mannering (2022b), out-of-sample simulations were employed to investigate temporal shifts in the injury severity related to distracted driving. The findings suggested that distracted driving crashes have become less severe over time according to both the latent-class multinomial logit model and a random parameters logit model with heterogeneity in the means and variances, while the latter model yielded significantly different injury-severity predictions. Yan et al. (2023) examined the temporal shifts and age-related variations in contributing factors that determined various injury severity levels in nighttime crashes and analyzed the disparities between out-of-sample and within-sample predictions. The findings revealed the instability in prediction directions among various age groups over time and highlighted the crucial need to account for temporal instability and age-related differences when predicting accident occurrences.

Concerning the driver injury severity modeling, multiple econometric approaches have been employed to investigate the contributing factors of crashes based on aggregated crash records or their subsets from a specific standpoint (Behnood and Mannering, 2016; Mannering et al., 2020; Yan et al., 2021a; Alnawmasi and Mannering, 2022). Discrete outcome models, such as the ordered probit models (Anarkooli and Hosseinlou, 2016), multinomial logit models (Wu et al., 2016), mixed logit models (Behnood and Mannering, 2015), and nested logit models (Xie et al., 2012), have been extensively utilized to identify determinants while considering the discrete nature of crash variables. However, these models with fixed parameters may not capture the heterogeneity across all observations when assuming the impacts of contributing factors on injury severities were the same (Behnood and Mannering, 2017). Subsequently, the econometric methods have continuously evolved from the basic fixed parameter models to sophisticated random parameter models. Some examples include grouped random parameters models (Ahmed et al., 2020), correlated random parameters models (Song et al., 2022), random parameters logit models (Alnawmasi and Mannering, 2022), random parameters tobit models

(Zeng et al., 2022), random thresholds random parameters models (Yan et al., 2021a), and random parameters hierarchical ordered probit models (Alzaffin et al., 2023). Various other alternative econometric models have also been applied, such as Markov switching count models (Malyshkina and Mannering, 2010) and latent class models (Behnood and Mannering, 2016; Chang et al., 2021; Kim, 2023).

To address the aforementioned research gaps and establish an explicit analytical framework for exploring the driver injury severity in single-vehicle crashes across different vehicle impact locations under adverse road surface conditions, the present study aims to: (a) identify observable factors affecting the driver injury severity for each disaggregated vehicle impact location (center/left/right) while effectively handling unobserved heterogeneity by using the random parameters logit modeling framework; (b) quantify and characterize the net effect of aggregate year-to-year and location-to-location shifts through probability differences between out-of-sample predictions and within-sample observations; and (c) investigate the temporal instability and impact location non-transferability of individual determinants on adverse-road-related driver injury severities across center, left-side, and right-side crashes. The remainder of this paper is structured as follows. Section 2 provides a descriptive statistical analysis of the dataset, and the methodological approach used in this study is introduced in Section 3. Section 4 presents the temporal stability and impact location transferability tests based on the likelihood ratio tests. Section 5 provides a detailed assessment of net effects caused by the temporal instability and impact location differences. The comprehensive discussion of the model estimation results for different impact locations across three years is presented in Section 6. Section 7 provides the conclusions, policy implications, and future research directions of this study.

## 2. Data description

The crash data utilized in the study is provided by the Highway Safety Information System, which contains single-vehicle crash records that occurred under adverse road surface conditions in Ohio from January 1, 2015, to December 31, 2017. In this research, adverse-road-related crashes refer to crashes that happen on wet, snowy, icy, or mud-sand road surfaces. Regarding the detailed classification of different vehicle impact locations, the “Center Front” and “Rear Center” samples are classified as the center crashes; the “Left Front”, “Left Side”, and “Left Rear” samples are identified as the left-side crashes; and the “Right Front”, “Right Side”, and “Right Rear” samples are categorized as the right-side crashes. Meanwhile, the accident sub-dataset and the vehicle sub-dataset are merged based on the corresponding accident identification number to comprehensively identify the determinants of driver injury severities over the observed years. After screening out observations with missing data in variables, the final dataset contains 12,013, 6,532, and 10,628 records for 2015, 2016, and 2017, respectively.

Three categories are utilized to represent driver injury severity outcomes: no injury, minor injury, and severe injury. Multiple variables including crash characteristics, driver characteristics, temporal characteristics, vehicle characteristics, roadway characteristics, and environment characteristics are identified as explanatory variables determining different levels of driver injury severities associated with adverse-road-related crashes. **Table 1 and Fig. 1** show the driver injury severity distribution of different vehicle impact locations by year (78.68%, 19.56%, and 1.76% for no injury, minor injury, and severe injury in total center crashes, 81.58%, 16.76%, and 1.66% in total left-side crashes, while 84.71%, 14.27%, and 1.02% in total right-side crashes). Specifically, center crashes make up the largest proportion of all injury levels throughout the observed years. It should be noted that the proportion of no injuries in center crashes is the smallest compared to that in left-side and right-side crashes. Typically, the proportions of minor and severe injuries in center and left-side crashes are greater than those in right-side crashes. **Table 2** presents the descriptive statistics of independent variables in the center, left-side, and right-side crashes across different years.

**Table 1.** Crash injury frequency distribution for impact locations by year.

| Year | Center crashes | | | Left-side crashes | | | Right-side crashes | | | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| | NI | MI | SI | NI | MI | SI | NI | MI | SI | |
| 2015 | 3455 | 871 | 73 | 3097 | 630 | 60 | 3280 | 517 | 30 | 12013 |
| 2016 | 1969 | 493 | 41 | 1605 | 338 | 25 | 1736 | 296 | 29 | 6532 |
| 2017 | 3254 | 793 | 80 | 2677 | 548 | 65 | 2692 | 485 | 34 | 10628 |

Remarks: NI = No Injury; MI = Minor Injury; SI = Severe Injury.

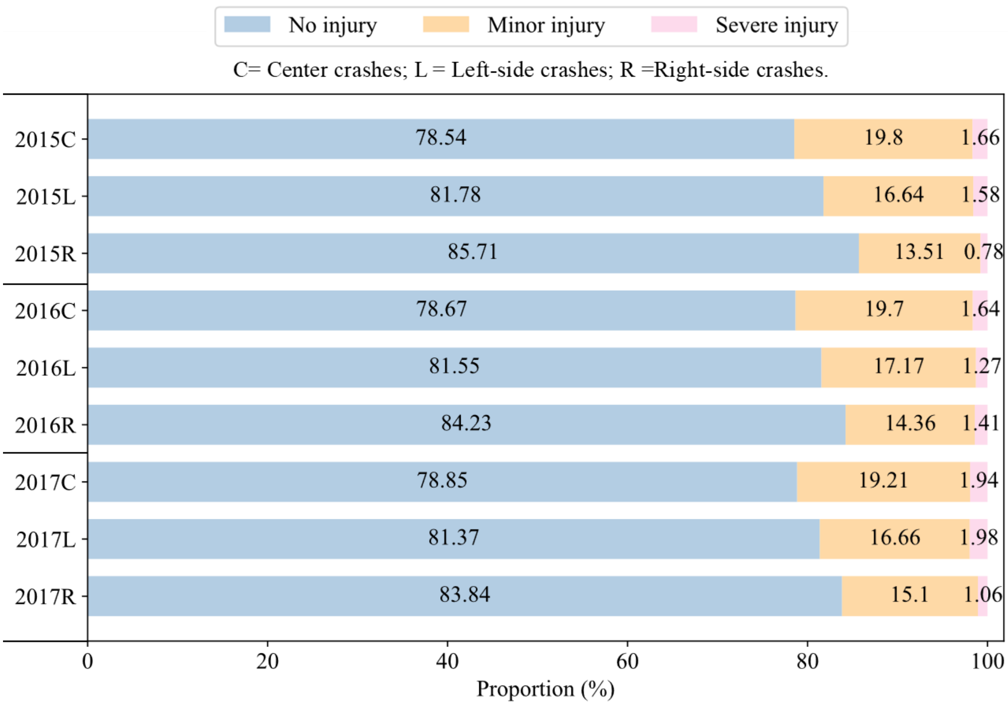



**Fig. 1.** Adverse-road-related crash injury severity distribution for different impact locations over the years.

**Table 2.** Descriptive statistics of independent variables (Std. Dev. in parentheses).

| Variables | IL | 2015 | | | 2016 | | | 2017 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | NI | MI | SI | NI | MI | SI | NI | MI | SI |
| **Crash characteristics** | | | | | | | | | | |
| Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | C | 0.744 (0.436) | 0.944 (0.230) | 0.973 (0.164) | 0.775 (0.418) | 0.917 (0.276) | 0.927 (0.264) | 0.743 (0.437) | 0.913 (0.282) | 0.937 (0.243) |
| | L | 0.751 (0.433) | 0.884 (0.320) | 0.950 (0.219) | 0.762 (0.426) | 0.893 (0.309) | 0.840 (0.374) | 0.729 (0.444) | 0.909 (0.288) | 0.923 (0.267) |
| | R | 0.798 (0.402) | 0.905 (0.293) | 0.900 (0.302) | 0.810 (0.392) | 0.892 (0.311) | 0.897 (0.310) | 0.790 (0.407) | 0.911 (0.284) | 1.000 (0.000) |
| Collision with non-fixed object indicator (1 if collided with non-fixed object as the first harmful event, 0 otherwise) | C | 0.223 (0.416) | 0.035 (0.184) | 0.000 (0.000) | 0.195 (0.396) | 0.034 (0.183) | 0.000 (0.000) | 0.225 (0.418) | 0.042 (0.200) | 0.050 (0.218) |
| | L | 0.186 (0.389) | 0.019 (0.138) | 0.017 (0.128) | 0.173 (0.378) | 0.030 (0.170) | 0.040 (0.200) | 0.217 (0.412) | 0.035 (0.183) | 0.000 (0.000) |
| | R | 0.147 (0.354) | 0.035 (0.184) | 0.000 (0.000) | 0.146 (0.353) | 0.030 (0.172) | 0.000 (0.000) | 0.157 (0.364) | 0.027 (0.162) | 0.000 (0.000) |
| Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | C | 0.033 (0.178) | 0.026 (0.160) | 0.027 (0.164) | 0.030 (0.171) | 0.049 (0.215) | 0.073 (0.264) | 0.031 (0.174) | 0.045 (0.208) | 0.013 (0.111) |
| | L | 0.064 (0.244) | 0.081 (0.273) | 0.033 (0.180) | 0.065 (0.247) | 0.077 (0.267) | 0.120 (0.332) | 0.054 (0.226) | 0.057 (0.231) | 0.077 (0.267) |
| | R | 0.055 (0.229) | 0.075 (0.264) | 0.100 (0.302) | 0.044 (0.206) | 0.078 (0.268) | 0.103 (0.310) | 0.053 (0.224) | 0.062 (0.241) | 0.000 (0.000) |
| Animal indicator (1 if animal involved in the crash, 0 otherwise) | C | 0.203 (0.402) | 0.022 (0.146) | 0.000 (0.000) | 0.176 (0.381) | 0.020 (0.141) | 0.000 (0.000) | 0.209 (0.406) | 0.033 (0.178) | 0.025 (0.156) |
| | L | 0.169 (0.374) | 0.029 (0.167) | 0.000 (0.000) | 0.158 (0.365) | 0.024 (0.152) | 0.000 (0.000) | 0.200 (0.400) | 0.026 (0.158) | 0.000 (0.000) |
| | R | 0.126 (0.332) | 0.015 (0.123) | 0.000 (0.000) | 0.126 (0.331) | 0.027 (0.162) | 0.000 (0.000) | 0.139 (0.346) | 0.023 (0.149) | 0.000 (0.000) |
| Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise) | C | 0.230 (0.421) | 0.056 (0.230) | 0.014 (0.117) | 0.203 (0.402) | 0.057 (0.232) | 0.000 (0.000) | 0.192 (0.394) | 0.052 (0.221) | 0.013 (0.111) |
| | L | 0.248 (0.432) | 0.063 (0.244) | 0.017 (0.128) | 0.229 (0.420) | 0.095 (0.293) | 0.080 (0.277) | 0.225 (0.418) | 0.051 (0.220) | 0.031 (0.173) |
| | R | 0.254 (0.435) | 0.093 (0.290) | 0.033 (0.181) | 0.258 (0.438) | 0.111 (0.315) | 0.069 (0.258) | 0.231 (0.422) | 0.060 (0.237) | 0.029 (0.170) |
| Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise) | C | 0.286 (0.452) | 0.166 (0.373) | 0.068 (0.253) | 0.270 (0.444) | 0.148 (0.356) | 0.049 (0.218) | 0.258 (0.437) | 0.122 (0.328) | 0.025 (0.156) |
| | L | 0.335 (0.472) | 0.198 (0.399) | 0.033 (0.180) | 0.326 (0.469) | 0.216 (0.412) | 0.040 (0.200) | 0.317 (0.465) | 0.188 (0.391) | 0.062 (0.241) |
| | R | 0.333 (0.471) | 0.195 (0.397) | 0.233 (0.425) | 0.312 (0.464) | 0.193 (0.395) | 0.034 (0.186) | 0.318 (0.466) | 0.179 (0.384) | 0.235 (0.426) |
| Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | C | 0.484 (0.500) | 0.777 (0.416) | 0.918 (0.275) | 0.527 (0.499) | 0.795 (0.404) | 0.951 (0.218) | 0.551 (0.497) | 0.826 (0.379) | 0.962 (0.190) |
| | L | 0.417 (0.493) | 0.738 (0.440) | 0.950 (0.219) | 0.445 (0.497) | 0.689 (0.463) | 0.880 (0.332) | 0.458 (0.498) | 0.761 (0.427) | 0.908 (0.290) |
| | R | 0.413 (0.492) | 0.712 (0.453) | 0.733 (0.445) | 0.430 (0.495) | 0.696 (0.461) | 0.897 (0.310) | 0.451 (0.498) | 0.761 (0.427) | 0.735 (0.443) |
| Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise) | C | 0.782 (0.413) | 0.750 (0.433) | 0.699 (0.460) | 0.743 (0.437) | 0.740 (0.439) | 0.780 (0.419) | 0.761 (0.427) | 0.715 (0.452) | 0.713 (0.454) |
| | L | 0.765 (0.424) | 0.730 (0.444) | 0.683 (0.466) | 0.748 (0.434) | 0.692 (0.462) | 0.640 (0.490) | 0.741 (0.438) | 0.730 (0.444) | 0.754 (0.432) |
| | R | 0.752 (0.432) | 0.721 (0.448) | 0.833 (0.375) | 0.762 (0.426) | 0.716 (0.452) | 0.586 (0.501) | 0.738 (0.440) | 0.711 (0.453) | 0.676 (0.470) |
| Other movements indicator (1 if vehicle was making turns or other movements preceding the crash, 0 otherwise) | C | 0.218 (0.413) | 0.250 (0.433) | 0.301 (0.460) | 0.257 (0.437) | 0.260 (0.439) | 0.220 (0.419) | 0.239 (0.427) | 0.285 (0.452) | 0.288 (0.454) |
| | L | 0.218 (0.413) | 0.250 (0.433) | 0.301 (0.460) | 0.252 (0.434) | 0.308 (0.462) | 0.360 (0.490) | 0.259 (0.438) | 0.270 (0.444) | 0.246 (0.432) |
| | R | 0.248 (0.432) | 0.279 (0.448) | 0.167 (0.375) | 0.238 (0.426) | 0.284 (0.452) | 0.414 (0.501) | 0.262 (0.440) | 0.289 (0.453) | 0.324 (0.470) |
| **Driver characteristics** | | | | | | | | | | |
| Young driver indicator (1 if driver age below 30 years, 0 otherwise) | C | 0.466 (0.499) | 0.514 (0.500) | 0.384 (0.487) | 0.493 (0.500) | 0.477 (0.500) | 0.366 (0.488) | 0.491 (0.500) | 0.488 (0.500) | 0.362 (0.482) |
| | L | 0.470 (0.499) | 0.483 (0.500) | 0.450 (0.499) | 0.485 (0.500) | 0.503 (0.501) | 0.480 (0.510) | 0.470 (0.499) | 0.474 (0.499) | 0.385 (0.488) |
| | R | 0.459 (0.498) | 0.509 (0.500) | 0.433 (0.498) | 0.463 (0.499) | 0.446 (0.498) | 0.379 (0.494) | 0.463 (0.499) | 0.468 (0.499) | 0.529 (0.502) |
| Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise) | C | 0.335 (0.472) | 0.290 (0.454) | 0.301 (0.460) | 0.311 (0.463) | 0.329 (0.470) | 0.317 (0.471) | 0.308 (0.462) | 0.333 (0.471) | 0.300 (0.459) |
| | L | 0.323 (0.468) | 0.343 (0.475) | 0.283 (0.452) | 0.334 (0.472) | 0.314 (0.465) | 0.280 (0.458) | 0.318 (0.466) | 0.356 (0.479) | 0.338 (0.474) |
| | R | 0.337 (0.473) | 0.296 (0.457) | 0.300 (0.461) | 0.331 (0.471) | 0.328 (0.470) | 0.414 (0.501) | 0.329 (0.470) | 0.320 (0.466) | 0.147 (0.356) |
| Old driver indicator (1 if driver age over 50, 0 otherwise) | C | 0.200 (0.400) | 0.195 (0.396) | 0.315 (0.466) | 0.197 (0.397) | 0.195 (0.396) | 0.317 (0.471) | 0.201 (0.401) | 0.179 (0.383) | 0.338 (0.474) |
| | L | 0.207 (0.405) | 0.175 (0.380) | 0.267 (0.443) | 0.181 (0.385) | 0.183 (0.388) | 0.240 (0.436) | 0.213 (0.409) | 0.170 (0.375) | 0.277 (0.449) |
| | R | 0.205 (0.404) | 0.195 (0.397) | 0.267 (0.445) | 0.206 (0.405) | 0.226 (0.419) | 0.207 (0.412) | 0.208 (0.406) | 0.212 (0.409) | 0.324 (0.470) |
| | C | 0.961 (0.193) | 0.878 (0.327) | 0.671 (0.471) | 0.957 (0.203) | 0.854 (0.354) | 0.537 (0.505) | 0.952 (0.213) | 0.860 (0.347) | 0.688 (0.464) |

| Variables | IL | 2015 | | | 2016 | | | 2017 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | NI | MI | SI | NI | MI | SI | NI | MI | SI |
| Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | L | 0.961 (0.195) | 0.894 (0.308) | 0.600 (0.491) | 0.958 (0.201) | 0.926 (0.262) | 0.640 (0.490) | 0.963 (0.188) | 0.903 (0.296) | 0.692 (0.463) |
| | R | 0.952 (0.213) | 0.882 (0.323) | 0.400 (0.493) | 0.959 (0.199) | 0.885 (0.319) | 0.414 (0.501) | 0.954 (0.210) | 0.868 (0.339) | 0.559 (0.499) |
| Gender indicator (1 if driver was female, 0 otherwise) | C | 0.373 (0.484) | 0.486 (0.500) | 0.466 (0.500) | 0.371 (0.483) | 0.454 (0.498) | 0.244 (0.435) | 0.377 (0.485) | 0.464 (0.499) | 0.412 (0.493) |
| | L | 0.376 (0.484) | 0.490 (0.500) | 0.317 (0.466) | 0.361 (0.480) | 0.485 (0.501) | 0.400 (0.500) | 0.369 (0.482) | 0.513 (0.500) | 0.446 (0.498) |
| | R | 0.371 (0.483) | 0.495 (0.500) | 0.333 (0.474) | 0.369 (0.483) | 0.524 (0.500) | 0.379 (0.494) | 0.372 (0.483) | 0.499 (0.500) | 0.500 (0.502) |
| Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | C | 0.059 (0.236) | 0.171 (0.377) | 0.338 (0.474) | 0.071 (0.256) | 0.181 (0.385) | 0.390 (0.494) | 0.058 (0.233) | 0.178 (0.382) | 0.413 (0.493) |
| | L | 0.059 (0.236) | 0.171 (0.377) | 0.338 (0.474) | 0.054 (0.226) | 0.121 (0.327) | 0.240 (0.436) | 0.059 (0.235) | 0.128 (0.334) | 0.215 (0.412) |
| | R | 0.067 (0.249) | 0.133 (0.340) | 0.289 (0.456) | 0.068 (0.252) | 0.122 (0.327) | 0.207 (0.412) | 0.060 (0.237) | 0.142 (0.349) | 0.294 (0.458) |
| **Temporal characteristics** | | | | | | | | | | |
| Weekday indicator (1 if crash occurred during the weekday, 0 otherwise) | C | 0.648 (0.478) | 0.659 (0.474) | 0.685 (0.466) | 0.682 (0.466) | 0.692 (0.462) | 0.561 (0.502) | 0.708 (0.455) | 0.728 (0.445) | 0.688 (0.464) |
| | L | 0.636 (0.481) | 0.654 (0.476) | 0.567 (0.497) | 0.685 (0.465) | 0.722 (0.449) | 0.560 (0.507) | 0.737 (0.440) | 0.728 (0.445) | 0.800 (0.401) |
| | R | 0.651 (0.477) | 0.660 (0.474) | 0.733 (0.445) | 0.696 (0.460) | 0.703 (0.458) | 0.759 (0.435) | 0.740 (0.439) | 0.720 (0.449) | 0.824 (0.383) |
| Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise) | C | 0.192 (0.394) | 0.166 (0.373) | 0.164 (0.371) | 0.196 (0.397) | 0.211 (0.408) | 0.220 (0.419) | 0.189 (0.391) | 0.197 (0.398) | 0.250 (0.434) |
| | L | 0.185 (0.388) | 0.175 (0.380) | 0.200 (0.401) | 0.186 (0.389) | 0.142 (0.350) | 0.240 (0.436) | 0.192 (0.394) | 0.170 (0.375) | 0.185 (0.389) |
| | R | 0.187 (0.390) | 0.149 (0.356) | 0.267 (0.445) | 0.184 (0.387) | 0.155 (0.363) | 0.172 (0.384) | 0.180 (0.384) | 0.190 (0.392) | 0.059 (0.236) |
| Morning indicator (1 if time of day is between 6AM to 11:59 AM, 0 otherwise) | C | 0.316 (0.465) | 0.323 (0.468) | 0.219 (0.415) | 0.268 (0.443) | 0.278 (0.448) | 0.244 (0.435) | 0.290 (0.454) | 0.290 (0.454) | 0.288 (0.454) |
| | L | 0.320 (0.467) | 0.329 (0.470) | 0.267 (0.443) | 0.312 (0.463) | 0.299 (0.458) | 0.280 (0.458) | 0.302 (0.459) | 0.325 (0.468) | 0.200 (0.401) |
| | R | 0.333 (0.471) | 0.358 (0.480) | 0.233 (0.425) | 0.309 (0.462) | 0.338 (0.474) | 0.241 (0.435) | 0.298 (0.457) | 0.334 (0.472) | 0.412 (0.495) |
| Afternoon indicator (1 if time of day is between 12 PM to 6:59 PM, 0 otherwise) | C | 0.271 (0.444) | 0.302 (0.459) | 0.370 (0.484) | 0.307 (0.461) | 0.296 (0.457) | 0.390 (0.494) | 0.279 (0.449) | 0.277 (0.448) | 0.250 (0.434) |
| | L | 0.284 (0.451) | 0.305 (0.460) | 0.333 (0.473) | 0.290 (0.454) | 0.355 (0.479) | 0.320 (0.476) | 0.278 (0.448) | 0.296 (0.456) | 0.308 (0.463) |
| | R | 0.268 (0.443) | 0.292 (0.455) | 0.300 (0.461) | 0.281 (0.450) | 0.307 (0.462) | 0.276 (0.455) | 0.299 (0.458) | 0.291 (0.454) | 0.324 (0.470) |
| Evening indicator (1 if time of day is between 7 PM to 11:59 PM, 0 otherwise) | C | 0.221 (0.415) | 0.209 (0.407) | 0.247 (0.432) | 0.230 (0.421) | 0.215 (0.411) | 0.146 (0.358) | 0.242 (0.428) | 0.236 (0.425) | 0.212 (0.410) |
| | L | 0.210 (0.407) | 0.192 (0.394) | 0.200 (0.401) | 0.213 (0.410) | 0.204 (0.404) | 0.160 (0.374) | 0.228 (0.420) | 0.210 (0.407) | 0.308 (0.463) |
| | R | 0.212 (0.409) | 0.201 (0.401) | 0.200 (0.402) | 0.226 (0.418) | 0.199 (0.400) | 0.310 (0.471) | 0.223 (0.416) | 0.186 (0.389) | 0.206 (0.406) |
| Spring indicator (1 if crash occurred during the spring, 0 otherwise) | C | 0.142 (0.349) | 0.162 (0.368) | 0.205 (0.405) | 0.190 (0.392) | 0.181 (0.385) | 0.146 (0.358) | 0.163 (0.370) | 0.199 (0.400) | 0.225 (0.418) |
| | L | 0.139 (0.345) | 0.176 (0.381) | 0.200 (0.401) | 0.177 (0.382) | 0.169 (0.375) | 0.240 (0.436) | 0.161 (0.368) | 0.159 (0.366) | 0.185 (0.389) |
| | R | 0.137 (0.344) | 0.172 (0.378) | 0.267 (0.445) | 0.181 (0.386) | 0.247 (0.432) | 0.172 (0.384) | 0.150 (0.357) | 0.210 (0.408) | 0.176 (0.383) |
| Summer indicator (1 if crash occurred during the summer, 0 otherwise) | C | 0.088 (0.284) | 0.123 (0.328) | 0.096 (0.295) | 0.105 (0.307) | 0.130 (0.336) | 0.049 (0.218) | 0.118 (0.323) | 0.134 (0.340) | 0.112 (0.317) |
| | L | 0.090 (0.286) | 0.114 (0.318) | 0.133 (0.341) | 0.108 (0.311) | 0.154 (0.361) | 0.080 (0.277) | 0.108 (0.310) | 0.128 (0.334) | 0.154 (0.362) |
| | R | 0.085 (0.279) | 0.108 (0.311) | 0.100 (0.302) | 0.113 (0.317) | 0.159 (0.366) | 0.207 (0.412) | 0.119 (0.324) | 0.163 (0.369) | 0.059 (0.236) |
| Autumn indicator (1 if crash occurred during the autumn, 0 otherwise) | C | 0.214 (0.410) | 0.207 (0.405) | 0.233 (0.424) | 0.318 (0.466) | 0.298 (0.458) | 0.268 (0.449) | 0.275 (0.446) | 0.231 (0.421) | 0.325 (0.469) |
| | L | 0.193 (0.395) | 0.187 (0.390) | 0.183 (0.388) | 0.320 (0.466) | 0.308 (0.462) | 0.400 (0.500) | 0.270 (0.444) | 0.228 (0.420) | 0.154 (0.362) |
| | R | 0.193 (0.395) | 0.162 (0.369) | 0.167 (0.375) | 0.308 (0.462) | 0.233 (0.424) | 0.207 (0.412) | 0.272 (0.445) | 0.227 (0.419) | 0.265 (0.443) |
| Winter indicator (1 if crash occurred during the winter, 0 otherwise) | C | 0.555 (0.497) | 0.509 (0.500) | 0.466 (0.500) | 0.386 (0.487) | 0.391 (0.489) | 0.537 (0.505) | 0.443 (0.497) | 0.436 (0.496) | 0.338 (0.474) |
| | L | 0.578 (0.494) | 0.522 (0.500) | 0.483 (0.501) | 0.395 (0.489) | 0.370 (0.483) | 0.280 (0.458) | 0.461 (0.499) | 0.485 (0.500) | 0.508 (0.501) |
| | R | 0.584 (0.493) | 0.557 (0.497) | 0.467 (0.502) | 0.397 (0.490) | 0.361 (0.481) | 0.414 (0.501) | 0.460 (0.498) | 0.400 (0.490) | 0.500 (0.502) |
| **Vehicle characteristics** | | | | | | | | | | |
| Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise) | C | 0.595 (0.491) | 0.637 (0.481) | 0.521 (0.501) | 0.597 (0.491) | 0.586 (0.493) | 0.415 (0.499) | 0.607 (0.488) | 0.608 (0.488) | 0.625 (0.485) |
| | L | 0.558 (0.497) | 0.492 (0.500) | 0.467 (0.500) | 0.535 (0.499) | 0.586 (0.493) | 0.600 (0.500) | 0.561 (0.496) | 0.558 (0.497) | 0.492 (0.501) |
| | R | 0.536 (0.499) | 0.569 (0.495) | 0.533 (0.502) | 0.544 (0.498) | 0.591 (0.492) | 0.517 (0.509) | 0.536 (0.499) | 0.528 (0.499) | 0.529 (0.502) |

| Variables | IL | 2015 | | | 2016 | | | 2017 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | NI | MI | SI | NI | MI | SI | NI | MI | SI |
| Truck involvement indicator (1 if truck being involved in the crash, 0 otherwise) | C | 0.226 (0.418) | 0.185 (0.388) | 0.315 (0.466) | 0.213 (0.410) | 0.221 (0.415) | 0.390 (0.494) | 0.207 (0.405) | 0.190 (0.393) | 0.163 (0.370) |
| | L | 0.258 (0.437) | 0.254 (0.435) | 0.333 (0.473) | 0.255 (0.436) | 0.213 (0.410) | 0.320 (0.476) | 0.238 (0.426) | 0.215 (0.411) | 0.308 (0.463) |
| | R | 0.263 (0.440) | 0.230 (0.421) | 0.333 (0.474) | 0.241 (0.428) | 0.179 (0.384) | 0.241 (0.435) | 0.271 (0.444) | 0.256 (0.436) | 0.206 (0.406) |
| Sport Utility Vehicle (SUV) involvement indicator (1 if SUV being involved in the crash, 0 otherwise) | C | 0.179 (0.384) | 0.178 (0.383) | 0.164 (0.371) | 0.189 (0.392) | 0.193 (0.395) | 0.195 (0.401) | 0.186 (0.389) | 0.202 (0.401) | 0.213 (0.410) |
| | L | 0.184 (0.388) | 0.254 (0.435) | 0.200 (0.401) | 0.211 (0.408) | 0.201 (0.401) | 0.080 (0.277) | 0.201 (0.401) | 0.226 (0.419) | 0.200 (0.401) |
| | R | 0.202 (0.401) | 0.201 (0.401) | 0.133 (0.342) | 0.215 (0.411) | 0.230 (0.421) | 0.241 (0.435) | 0.193 (0.395) | 0.216 (0.412) | 0.265 (0.443) |
| Insurance indicator (1 if vehicle was insured, 0 otherwise) | C | 0.823 (0.382) | 0.698 (0.459) | 0.493 (0.501) | 0.815 (0.388) | 0.659 (0.474) | 0.585 (0.499) | 0.814 (0.389) | 0.653 (0.476) | 0.525 (0.500) |
| | L | 0.836 (0.370) | 0.759 (0.428) | 0.483 (0.501) | 0.829 (0.376) | 0.692 (0.462) | 0.600 (0.500) | 0.843 (0.364) | 0.719 (0.450) | 0.569 (0.496) |
| | R | 0.837 (0.369) | 0.735 (0.441) | 0.633 (0.485) | 0.824 (0.381) | 0.757 (0.430) | 0.621 (0.494) | 0.821 (0.384) | 0.703 (0.457) | 0.618 (0.488) |
| Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise) | C | 0.222 (0.416) | 0.147 (0.354) | 0.137 (0.345) | 0.201 (0.401) | 0.142 (0.349) | 0.024 (0.156) | 0.241 (0.428) | 0.193 (0.395) | 0.300 (0.459) |
| | L | 0.232 (0.422) | 0.170 (0.376) | 0.100 (0.301) | 0.201 (0.401) | 0.136 (0.343) | 0.160 (0.374) | 0.277 (0.448) | 0.193 (0.395) | 0.154 (0.362) |
| | R | 0.217 (0.412) | 0.157 (0.364) | 0.333 (0.474) | 0.194 (0.395) | 0.159 (0.366) | 0.034 (0.186) | 0.256 (0.436) | 0.204 (0.403) | 0.176 (0.383) |
| Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise) | C | 0.320 (0.466) | 0.312 (0.464) | 0.329 (0.471) | 0.306 (0.461) | 0.325 (0.469) | 0.341 (0.480) | 0.271 (0.445) | 0.241 (0.428) | 0.188 (0.391) |
| | L | 0.323 (0.467) | 0.308 (0.462) | 0.267 (0.443) | 0.317 (0.465) | 0.266 (0.443) | 0.280 (0.458) | 0.245 (0.430) | 0.248 (0.432) | 0.200 (0.401) |
| | R | 0.334 (0.472) | 0.288 (0.453) | 0.233 (0.425) | 0.322 (0.467) | 0.284 (0.452) | 0.069 (0.258) | 0.245 (0.430) | 0.227 (0.419) | 0.294 (0.458) |
| Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise) | C | 0.458 (0.498) | 0.541 (0.498) | 0.534 (0.500) | 0.493 (0.500) | 0.533 (0.499) | 0.634 (0.488) | 0.488 (0.500) | 0.566 (0.496) | 0.513 (0.501) |
| | L | 0.446 (0.497) | 0.522 (0.500) | 0.633 (0.483) | 0.482 (0.500) | 0.598 (0.491) | 0.560 (0.507) | 0.477 (0.500) | 0.558 (0.497) | 0.646 (0.479) |
| | R | 0.449 (0.497) | 0.555 (0.497) | 0.433 (0.498) | 0.484 (0.500) | 0.557 (0.498) | 0.897 (0.310) | 0.500 (0.500) | 0.569 (0.495) | 0.529 (0.502) |
| **Roadway characteristics** | | | | | | | | | | |
| Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | C | 0.831 (0.375) | 0.815 (0.388) | 0.822 (0.383) | 0.834 (0.372) | 0.811 (0.392) | 0.805 (0.401) | 0.838 (0.368) | 0.830 (0.376) | 0.937 (0.243) |
| | L | 0.834 (0.372) | 0.813 (0.390) | 0.900 (0.301) | 0.832 (0.374) | 0.861 (0.347) | 0.800 (0.408) | 0.858 (0.349) | 0.836 (0.371) | 0.831 (0.376) |
| | R | 0.830 (0.376) | 0.843 (0.364) | 0.800 (0.402) | 0.840 (0.367) | 0.831 (0.375) | 0.966 (0.186) | 0.863 (0.344) | 0.837 (0.369) | 0.882 (0.324) |
| The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise) | C | 0.446 (0.497) | 0.397 (0.489) | 0.411 (0.493) | 0.441 (0.497) | 0.444 (0.497) | 0.561 (0.502) | 0.447 (0.497) | 0.372 (0.483) | 0.538 (0.500) |
| | L | 0.409 (0.492) | 0.368 (0.482) | 0.467 (0.500) | 0.411 (0.492) | 0.411 (0.493) | 0.440 (0.507) | 0.405 (0.491) | 0.378 (0.485) | 0.523 (0.501) |
| | R | 0.473 (0.499) | 0.507 (0.500) | 0.467 (0.502) | 0.494 (0.500) | 0.490 (0.501) | 0.586 (0.501) | 0.467 (0.499) | 0.474 (0.500) | 0.412 (0.495) |
| The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise) | C | 0.499 (0.500) | 0.502 (0.500) | 0.507 (0.501) | 0.496 (0.500) | 0.475 (0.500) | 0.366 (0.488) | 0.492 (0.500) | 0.530 (0.499) | 0.387 (0.488) |
| | L | 0.537 (0.499) | 0.576 (0.494) | 0.483 (0.501) | 0.521 (0.500) | 0.515 (0.501) | 0.440 (0.507) | 0.524 (0.499) | 0.533 (0.499) | 0.338 (0.474) |
| | R | 0.478 (0.500) | 0.449 (0.498) | 0.500 (0.503) | 0.455 (0.498) | 0.439 (0.497) | 0.345 (0.484) | 0.481 (0.500) | 0.462 (0.499) | 0.529 (0.502) |
| The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | C | 0.054 (0.227) | 0.101 (0.301) | 0.082 (0.275) | 0.063 (0.243) | 0.081 (0.273) | 0.073 (0.264) | 0.061 (0.240) | 0.098 (0.298) | 0.075 (0.264) |
| | L | 0.054 (0.225) | 0.056 (0.229) | 0.050 (0.219) | 0.068 (0.252) | 0.074 (0.262) | 0.120 (0.332) | 0.070 (0.256) | 0.089 (0.285) | 0.138 (0.346) |
| | R | 0.049 (0.215) | 0.044 (0.206) | 0.033 (0.181) | 0.051 (0.221) | 0.071 (0.257) | 0.069 (0.258) | 0.051 (0.221) | 0.064 (0.245) | 0.059 (0.236) |
| Freeway indicator (1 if crash occurred on the freeway, 0 otherwise) | C | 0.432 (0.495) | 0.467 (0.499) | 0.452 (0.499) | 0.426 (0.495) | 0.430 (0.496) | 0.220 (0.419) | 0.436 (0.496) | 0.502 (0.500) | 0.300 (0.459) |
| | L | 0.472 (0.499) | 0.497 (0.500) | 0.400 (0.491) | 0.447 (0.497) | 0.491 (0.501) | 0.360 (0.490) | 0.472 (0.499) | 0.511 (0.500) | 0.431 (0.496) |
| | R | 0.403 (0.490) | 0.381 (0.486) | 0.300 (0.461) | 0.376 (0.484) | 0.372 (0.484) | 0.310 (0.471) | 0.408 (0.491) | 0.408 (0.492) | 0.382 (0.488) |
| Speed limit <30 mph indicator (1 if speed limit < 30 mph, 0 otherwise) | C | 0.045 (0.207) | 0.059 (0.235) | 0.041 (0.199) | 0.041 (0.197) | 0.034 (0.183) | 0.049 (0.218) | 0.039 (0.193) | 0.061 (0.239) | 0.075 (0.264) |
| | L | 0.036 (0.187) | 0.025 (0.157) | 0.033 (0.180) | 0.023 (0.150) | 0.018 (0.132) | 0.000 (0.000) | 0.029 (0.168) | 0.027 (0.163) | 0.015 (0.123) |
| | R | 0.049 (0.216) | 0.046 (0.210) | 0.000 (0.000) | 0.050 (0.218) | 0.034 (0.181) | 0.034 (0.186) | 0.040 (0.196) | 0.047 (0.213) | 0.000 (0.000) |
| Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise) | C | 0.675 (0.469) | 0.688 (0.464) | 0.808 (0.395) | 0.689 (0.463) | 0.728 (0.445) | 0.805 (0.401) | 0.678 (0.467) | 0.668 (0.471) | 0.713 (0.454) |
| | L | 0.643 (0.479) | 0.689 (0.463) | 0.717 (0.452) | 0.687 (0.464) | 0.704 (0.457) | 0.720 (0.458) | 0.654 (0.476) | 0.659 (0.474) | 0.754 (0.432) |
| | R | 0.666 (0.472) | 0.712 (0.453) | 0.833 (0.375) | 0.687 (0.464) | 0.696 (0.461) | 0.724 (0.455) | 0.669 (0.470) | 0.699 (0.459) | 0.853 (0.356) |

| **Variables** | **IL** | **2015** | | | **2016** | | | **2017** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | **NI** | **MI** | **SI** | **NI** | **MI** | **SI** | **NI** | **MI** | **SI** |
| Speed limit >60 mph indicator (1 if speed limit > 60 mph, 0 otherwise) | C | 0.280 (0.449) | 0.254 (0.435) | 0.151 (0.359) | 0.271 (0.444) | 0.237 (0.426) | 0.146 (0.358) | 0.283 (0.451) | 0.271 (0.445) | 0.213 (0.410) |
| | L | 0.321 (0.467) | 0.286 (0.452) | 0.250 (0.434) | 0.290 (0.454) | 0.278 (0.449) | 0.280 (0.458) | 0.317 (0.465) | 0.314 (0.464) | 0.231 (0.422) |
| | R | 0.285 (0.452) | 0.242 (0.428) | 0.167 (0.375) | 0.263 (0.441) | 0.270 (0.445) | 0.241 (0.435) | 0.290 (0.454) | 0.254 (0.435) | 0.147 (0.356) |
| Rural state indicator (1 if crash occurred in the rural state, 0 otherwise) | C | 0.662 (0.473) | 0.551 (0.497) | 0.548 (0.499) | 0.638 (0.481) | 0.584 (0.493) | 0.659 (0.480) | 0.645 (0.478) | 0.540 (0.499) | 0.588 (0.493) |
| | L | 0.657 (0.475) | 0.629 (0.483) | 0.617 (0.488) | 0.652 (0.477) | 0.636 (0.482) | 0.560 (0.507) | 0.653 (0.476) | 0.617 (0.486) | 0.723 (0.449) |
| | R | 0.679 (0.467) | 0.669 (0.471) | 0.767 (0.425) | 0.653 (0.476) | 0.645 (0.479) | 0.655 (0.484) | 0.673 (0.469) | 0.629 (0.483) | 0.676 (0.470) |
| Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise) | C | 0.308 (0.462) | 0.421 (0.494) | 0.452 (0.499) | 0.341 (0.474) | 0.400 (0.490) | 0.341 (0.480) | 0.323 (0.468) | 0.425 (0.494) | 0.387 (0.488) |
| | L | 0.305 (0.460) | 0.335 (0.472) | 0.350 (0.478) | 0.334 (0.472) | 0.340 (0.474) | 0.400 (0.500) | 0.314 (0.464) | 0.352 (0.478) | 0.262 (0.441) |
| | R | 0.287 (0.452) | 0.306 (0.461) | 0.233 (0.425) | 0.329 (0.470) | 0.331 (0.471) | 0.310 (0.471) | 0.290 (0.454) | 0.332 (0.471) | 0.324 (0.470) |
| Turnpike indicator (1 if crash occurred on the turnpike, 0 otherwise) | C | 0.030 (0.172) | 0.028 (0.164) | 0.000 (0.000) | 0.020 (0.141) | 0.016 (0.126) | 0.000 (0.000) | 0.032 (0.176) | 0.035 (0.185) | 0.025 (0.156) |
| | L | 0.038 (0.191) | 0.037 (0.188) | 0.033 (0.180) | 0.014 (0.119) | 0.024 (0.152) | 0.040 (0.200) | 0.033 (0.178) | 0.031 (0.173) | 0.015 (0.123) |
| | R | 0.034 (0.182) | 0.025 (0.157) | 0.000 (0.000) | 0.018 (0.132) | 0.024 (0.152) | 0.034 (0.186) | 0.037 (0.188) | 0.039 (0.194) | 0.000 (0.000) |
| Intersection indicator (1 if crash occurred on the intersection, 0 otherwise) | C | 0.318 (0.466) | 0.359 (0.480) | 0.342 (0.476) | 0.315 (0.465) | 0.333 (0.472) | 0.146 (0.358) | 0.326 (0.469) | 0.371 (0.483) | 0.250 (0.434) |
| | L | 0.362 (0.481) | 0.371 (0.483) | 0.300 (0.460) | 0.337 (0.473) | 0.367 (0.483) | 0.320 (0.476) | 0.355 (0.478) | 0.385 (0.487) | 0.262 (0.441) |
| | R | 0.309 (0.462) | 0.282 (0.450) | 0.133 (0.342) | 0.274 (0.446) | 0.291 (0.455) | 0.241 (0.435) | 0.309 (0.462) | 0.309 (0.462) | 0.176 (0.383) |
| **Environment characteristics** | | | | | | | | | | |
| Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise) | C | 0.661 (0.473) | 0.674 (0.469) | 0.603 (0.490) | 0.691 (0.462) | 0.682 (0.466) | 0.537 (0.505) | 0.687 (0.464) | 0.686 (0.464) | 0.587 (0.493) |
| | L | 0.683 (0.465) | 0.687 (0.464) | 0.567 (0.497) | 0.678 (0.467) | 0.598 (0.491) | 0.640 (0.490) | 0.683 (0.465) | 0.703 (0.457) | 0.662 (0.474) |
| | R | 0.685 (0.464) | 0.704 (0.457) | 0.667 (0.474) | 0.688 (0.464) | 0.628 (0.484) | 0.621 (0.494) | 0.699 (0.459) | 0.666 (0.472) | 0.647 (0.480) |
| Daylight indicator (1 if lighting condition is daylight, 0 otherwise) | C | 0.442 (0.497) | 0.505 (0.500) | 0.425 (0.495) | 0.432 (0.495) | 0.456 (0.499) | 0.488 (0.506) | 0.415 (0.493) | 0.470 (0.499) | 0.425 (0.495) |
| | L | 0.460 (0.498) | 0.535 (0.499) | 0.500 (0.501) | 0.460 (0.499) | 0.530 (0.500) | 0.400 (0.500) | 0.426 (0.495) | 0.511 (0.500) | 0.369 (0.484) |
| | R | 0.459 (0.498) | 0.563 (0.496) | 0.467 (0.502) | 0.461 (0.499) | 0.530 (0.500) | 0.448 (0.506) | 0.447 (0.497) | 0.495 (0.500) | 0.588 (0.495) |
| Dawn/dusk indicator (1 if lighting condition is dawn/dusk, 0 otherwise) | C | 0.062 (0.241) | 0.069 (0.253) | 0.068 (0.253) | 0.067 (0.249) | 0.069 (0.254) | 0.000 (0.000) | 0.063 (0.243) | 0.049 (0.216) | 0.050 (0.218) |
| | L | 0.062 (0.242) | 0.043 (0.203) | 0.067 (0.250) | 0.068 (0.252) | 0.038 (0.193) | 0.000 (0.000) | 0.065 (0.246) | 0.064 (0.245) | 0.108 (0.311) |
| | R | 0.066 (0.248) | 0.046 (0.210) | 0.033 (0.181) | 0.059 (0.235) | 0.091 (0.288) | 0.103 (0.310) | 0.061 (0.240) | 0.072 (0.259) | 0.088 (0.285) |
| Dark-lighted indicator (1 if lighting condition is dark-lighted, 0 otherwise) | C | 0.151 (0.358) | 0.194 (0.396) | 0.233 (0.424) | 0.176 (0.381) | 0.207 (0.405) | 0.220 (0.419) | 0.170 (0.376) | 0.240 (0.427) | 0.213 (0.410) |
| | L | 0.143 (0.350) | 0.179 (0.384) | 0.183 (0.388) | 0.163 (0.370) | 0.160 (0.367) | 0.280 (0.458) | 0.163 (0.370) | 0.181 (0.385) | 0.138 (0.346) |
| | R | 0.143 (0.350) | 0.149 (0.356) | 0.233 (0.425) | 0.153 (0.360) | 0.142 (0.350) | 0.138 (0.351) | 0.159 (0.366) | 0.171 (0.377) | 0.029 (0.170) |
| Dark-unlighted indicator (1 if lighting condition is dark-unlighted, 0 otherwise) | C | 0.346 (0.476) | 0.232 (0.422) | 0.274 (0.447) | 0.326 (0.469) | 0.268 (0.443) | 0.293 (0.461) | 0.352 (0.478) | 0.241 (0.428) | 0.313 (0.464) |
| | L | 0.334 (0.472) | 0.243 (0.429) | 0.250 (0.434) | 0.308 (0.462) | 0.272 (0.446) | 0.320 (0.476) | 0.346 (0.476) | 0.245 (0.430) | 0.385 (0.488) |
| | R | 0.332 (0.471) | 0.242 (0.428) | 0.267 (0.445) | 0.328 (0.470) | 0.236 (0.426) | 0.310 (0.471) | 0.333 (0.471) | 0.262 (0.440) | 0.294 (0.458) |

Remarks: IL = Impact Location; SI = Severe Injury; MI = Minor Injury; NI = No Injury; C = Center crashes; L = Left-side crashes; R = Right-side crashes.

## 3. Methodology

The random parameters multinomial logit model with the heterogeneity in the means and variances can explicitly address observation-related variations of explanatory variables although existing data sources cover only a small fraction of a wide variety of factors that affect the injury severities (Behnood and Mannering, 2017). To investigate significant contributing factors and identify the possible unobserved heterogeneity in adverse-road-related crashes, this model is employed in this study. The linear injury-severity function is defined as follows to determine the specific injury severity level *k* in crash *n* (Alnawmasi and Mannering, 2019):

$$U_{kn} = \boldsymbol{\beta}_k \boldsymbol{X}_{kn} + \varepsilon_{kn} \quad (1)$$

where $U_{kn}$ is the severity function that determines the probability of injury severity level *k* in crash *n*, $\boldsymbol{\beta}_k$ is the vector of parameters estimated for the driver injury severity level *k*, $\boldsymbol{X}_{kn}$ is the vector of explanatory variables influencing driver injury severities in single-vehicle crash *n*, and $\varepsilon_{kn}$ is a stochastic error term.

If the disturbance term is assumed to be generalized extreme value distributed, which allows parameters to vary across observations, a standard multinomial logit model can be defined as (McFadden, 1981):

$$P_{kn} = \int \frac{\exp(\boldsymbol{\beta}_k \boldsymbol{X}_{kn})}{\sum \exp(\boldsymbol{\beta}_k \boldsymbol{X}_{kn})} f(\boldsymbol{\beta}|\boldsymbol{\varphi}) d\boldsymbol{\beta} \quad (2)$$

where $P_{kn}$ is the probability of injury severity outcome $k$ in crash *n*, $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the probability density function of vector $\boldsymbol{\beta}$ and $\boldsymbol{\varphi}$ is a vector of parameters describing the density function, while the other terms have been defined previously.

When the heterogeneity in means and variances exists among random parameters, the vector $\boldsymbol{\beta}_{kn}$ that allows estimated parameters to vary across accidents can be defined as (Al-Bdairi et al., 2020; Islam and Mannering, 2020; Alnawmasi and Mannering, 2023):

$$\boldsymbol{\beta}_{kn} = \boldsymbol{\beta}_k + \boldsymbol{\delta}_k \boldsymbol{Z}_{kn} + \sigma_k \exp(\boldsymbol{\omega}_k \boldsymbol{W}_{kn}) \upsilon_{kn} \quad (3)$$

where $\boldsymbol{\beta}_k$ represents the constant term (constant across all observations for injury severity *k*), $\boldsymbol{Z}_{kn}$ is the vector of crash-specific variables with the heterogeneity in the mean that determines the driver injury severity *k*, $\boldsymbol{\delta}_k$ is a corresponding vector of estimable parameters, $\boldsymbol{W}_{kn}$ is another vector of crash-specific explanatory variables explaining the heterogeneity in the standard deviation $\sigma_k$ with the corresponding parameter vector $\boldsymbol{\omega}_k$, and $\upsilon_{kn}$ is the error term.

A simulation-based maximum likelihood method is used to estimate the model parameters. Previous studies (Halton, 1960; Bhat, 2000; Behnood and Al-Bdairi, 2020) have shown that 1000 Halton draws could effectively estimate coefficients for the distribution of the random parameters and compute the probabilities by stochastically drawing values. Meanwhile, a variety of parameter density functions (e.g., uniform, lognormal, normal, and triangular distributions) have been empirically evaluated in previous studies, which recommended that the model with a normal distribution is statistically superior in its capability to describe the central tendency and variations of random variables compared to models using other distributions (Behnood and Al-Bdairi, 2020; Islam and Mannering, 2020). Therefore, the identified random parameters are set to be normally distributed in this study.

To directly interpret the effects of significant variables $X_{kn}$ on the probability of driver injury outcome $k$, marginal effects are also computed**.** Specifically, the marginal effect denotes the effect that every one-unit increase of an explanatory variable $X_{knl}$ has on the $k$-th severity outcome probability (Washington et al., 2020), which is calculated by averaging the marginal effects over all crash observations:

$$\frac{\partial P_{kn}}{\partial X_{knl}} = \overline{P_{kn}}\ [\text{given } X_{knl} = 1] - \overline{P_{kn}}\ [\text{given } X_{knl} = 0] \tag{4}$$

## 4. Temporal stability and impact location transferability tests

To statistically investigate the stability of the influence that significant determinants have on adverse-road-related crash injury severities, two groups of likelihood ratio tests were conducted. The first series were employed to compare the models developed for two individual years and examine if the parameter estimates of the center, left-side, and right-side crash injury severities were stable over observed years, which can be defined as (Washington et al., 2020):

$$\chi_l^2 = -2[LL(\beta_{year_2 year_1}) - LL(\beta_{year_1})] \tag{5}$$

where $year_1$ and $year_2$ are two observed individual years; $LL(\beta_{year_2 year_1})$ is the log-likelihood of a model containing converged parameters from $year_2$ while using data from $year_1$; $LL(\beta_{year_1})$ is the log-likelihood at convergence of the model containing converged parameters using $year_1$'s data (parameters are no longer restricted to subset data $year_2$'s converged parameters as is the case for $LL(\beta_{year_2 year_1})$). The test was also conducted by reversing $year_1$'s data and $year_2$'s data to provide two test results for each model comparison. The test follows a $\chi^2$ distribution with the degrees of freedom equaling to the number of estimated parameters in $\beta_{year_2 year_1}$. The resulting $\chi^2$ statistic can be utilized to determine whether the null hypothesis that the parameters are stable in the two years should be rejected or accepted (Behnood and Mannering, 2015). **Table 3** presents the results of hypothesis tests across different collision locations over the years. There is a significant level of confidence that the models' specifications and estimated parameters are not temporally stable among the year-to-year combinations, as shown by the fact that 17 out of the 18 tests produced confidence levels that were larger than 99%. Besides, one test of year-on-year comparison illustrated that the null hypothesis (the parameters were the same) could be rejected at the 95% confidence level (this was the 2016 data using the 2015 parameter estimates for right-side crashes). As such, the overall high degree of confidence indicates the obvious temporal instability of the estimated parameters for each impact location group.

**Table 3.** Likelihood ratio test results for center, left-side, and right-side crashes between different years ($\chi^2$ values with degrees of freedom in parenthesis and confidence level in brackets).

| *$year_1$* | *$year_2$* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Center | | | Left | | | Right | | |
| | 2015 | 2016 | 2017 | 2015 | 2016 | 2017 | 2015 | 2016 | 2017 |
| 2015 | - | 71.874 | 71.657 | - | 88.868 | 52.350 | - | 85.035 | 62.994 |
| | - | (20) | (19) | - | (18) | (22) | - | (17) | (20) |
| | - | [>99.99%] | [>99.99%] | - | [>99.99%] | [99.97%] | - | [>99.99%] | [>99.99%] |
| 2016 | 91.705 | - | 48.474 | 47.159 | - | 43.827 | 35.400 | - | 62.860 |
| | (20) | - | (19) | (21) | - | (22) | (21) | - | (20) |
| | [>99.99%] | - | [99.98%] | [99.91%] | - | [99.63%] | [97.45%] | - | [>99.99%] |
| 2017 | 70.870 | 78.947 | - | 45.978 | 108.294 | - | 41.909 | 70.153 | - |
| | (20) | (20) | - | (21) | (18) | - | (21) | (17) | - |
| | [>99.99%] | [>99.99%] | - | [99.87%] | [>99.99%] | - | [99.57%] | [>99.99%] | - |

**Table 4.** Likelihood ratio test results for three years between different vehicle impact locations ($\chi^2$ values with degrees of freedom in parenthesis and confidence level in brackets).

| $l_1$ | $l_2$ | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 2015 | | | 2016 | | | 2017 | | |
| | Center | Left | Right | Center | Left | Right | Center | Left | Right |
| Center | - | 99.466 | 265.846 | - | 55.997 | 118.057 | - | 66.840 | 163.156 |
| | - | (21) | (21) | - | (18) | (17) | - | (22) | (20) |
| | - | [99.99%] | [>99.99%] | - | [>99.99%] | [>99.99%] | - | [>99.99%] | [>99.99%] |
| Left | 72.904 | - | 145.173 | 44.915 | - | 59.782 | 58.748 | - | 107.861 |
| | (20) | - | (21) | (20) | - | (17) | (19) | - | (20) |
| | [>99.99%] | - | [>99.99%] | [99.89%] | - | [>99.99%] | [>99.99%] | - | [>99.99%] |
| Right | 172.275 | 115.310 | - | 80.736 | 58.117 | - | 103.322 | 87.045 | - |
| | (20) | (21) | - | (20) | (18) | - | (19) | (22) | - |
| | [>99.99%] | [>99.99%] | - | [>99.99%] | [>99.99%] | - | [>99.99%] | [>99.99%] | - |

Similarly, the transferability of estimated parameters between center, left-side, and right-side crash models can be validated with (Alnawmasi and Mannering, 2022b):

$$\chi_t{}^2 = -2[LL(\beta_{l_2 l_1}) - LL(\beta_{l_1})] \tag{6}$$

where $l_1$ and $l_2$ are two individual vehicle impact locations; $LL(\beta_{l_2 l_1})$ is the log-likelihood of a model containing converged parameters from $l_2$ while using data from $l_1$; $LL(\beta_{l_1})$ is the log-likelihood at convergence of the model containing converged parameters using $l_1$'s data (parameters are no longer restricted to subset data $l_2$'s converged parameters as is the case for $LL(\beta_{l_2 l_1})$). **Table 4** presents the results of hypothesis tests for three years between different vehicle impact locations. These tests consistently yielded confidence levels exceeding 99%, indicating a substantial lack of transferability in the models' specifications and estimated parameters across different location combinations. Therefore, the null hypothesis that center, left-side, and right-side crash models can be transferred to each other should be rejected.

## 5. Net effect between out-of-sample predictions and within-sample observations

Examining the net effect of temporal shifts could provide more insightful results than solely focusing on likelihood ratio tests or marginal effects (Alnawmasi et al., 2024; Alnawmasi and Mannering, 2022a, 2022b; Hou et al., 2022; Xu et al., 2021). To this end, the out-of-sample prediction was first conducted. That is, parameters of one year's center/left-side/right-side crash model were used to predict the driver injury severity with center/left-side/right-side data from a different year. Meanwhile, the within-sample observation (the calculated probability from one year's data using the same year's estimated model) was also obtained to provide the comparison benchmark. The simulation of out-of-sample prediction was carried out using the similar method in estimating parameters from the base sample, and 1,000 Halton draws were employed to compute driver injury severity probabilities (Yan et al., 2023). The means of differences between the out-of-sample probability and within-sample probability could reveal the aggregate net effects of year-to-year temporal shifts, which are calculated through:

$$\Delta P\ (k_l) = P_{year_2 year_1}\ (k_l) - P_{year_1}\ (k_l) \tag{7}$$

where $P_{year_2 year_1}(k_l)$ is the estimated probability of the driver injury severity $k$ belonging to location category $l$ (center/left/right) in $year_2$ (2015/2016/2017) using the estimated injury severity model based on $year_1$'s (2015 or 2016) data, and $P_{year_1}\ (k_l)$ denotes the probability of the injury severity $k$ of location category $l$ in $year_1$ using $year_1$'s estimated model.

Likewise, to assess the aggregate injury severity differences among location-to-location (center/left-side/right-side) combinations, parameters of one group's crash model will be used to predict the driver injury severity probabilities with the other two groups' data in the same year. The means of differences between the out-of-sample probability and within-sample probability for each year can be calculated as:

$$\Delta P\ (k_{year}) = P_{l_2 l_1}\ (k_{year})\ -\ P_{l_1}\ (k_{year}) \tag{8}$$

where $P_{l_2 l_1}\ (k_{year})$ is the estimated probability of driver injury severity $k$ belonging to *year* (2015/2016/2017) in location category $l_2$ (center/left-side/right-side) using the estimated driver injury severity model based on $l_1$'s (center/left-side/right-side) data, and $P_{l_1}\ (k_{year})$ denotes the probability of injury severity $k$ of location category $l_1$ in *year* (2015/2016/2017) using the $l_1$'s estimated model.

**Table 5.** Means of probability differences in predicting the injury severity between different years.

| Observed year | Severity | Predicted year | | | | | |
|---|---|---|---|---|---|---|---|
| | | 2016 | | | 2017 | | |
| | | Center | Left | Right | Center | Left | Right |
| 2015 | NI | –0.0176 | –0.0060 | 0.0054 | –0.0176 | 0.0043 | 0.0072 |
| | MI | 0.0158 | 0.0030 | 0.0003 | 0.0195 | –0.0001 | –0.0050 |
| | SI | 0.0018 | 0.0030 | –0.0057 | –0.0019 | –0.0042 | –0.0022 |
| 2016 | NI | - | - | - | 0.0004 | 0.0026 | 0.0013 |
| | MI | - | - | - | 0.0027 | 0.0048 | –0.0054 |
| | SI | - | - | - | –0.0031 | –0.0074 | 0.0041 |

**Table 6.** Means of probability differences in predicting the injury severity between different impact location groups.

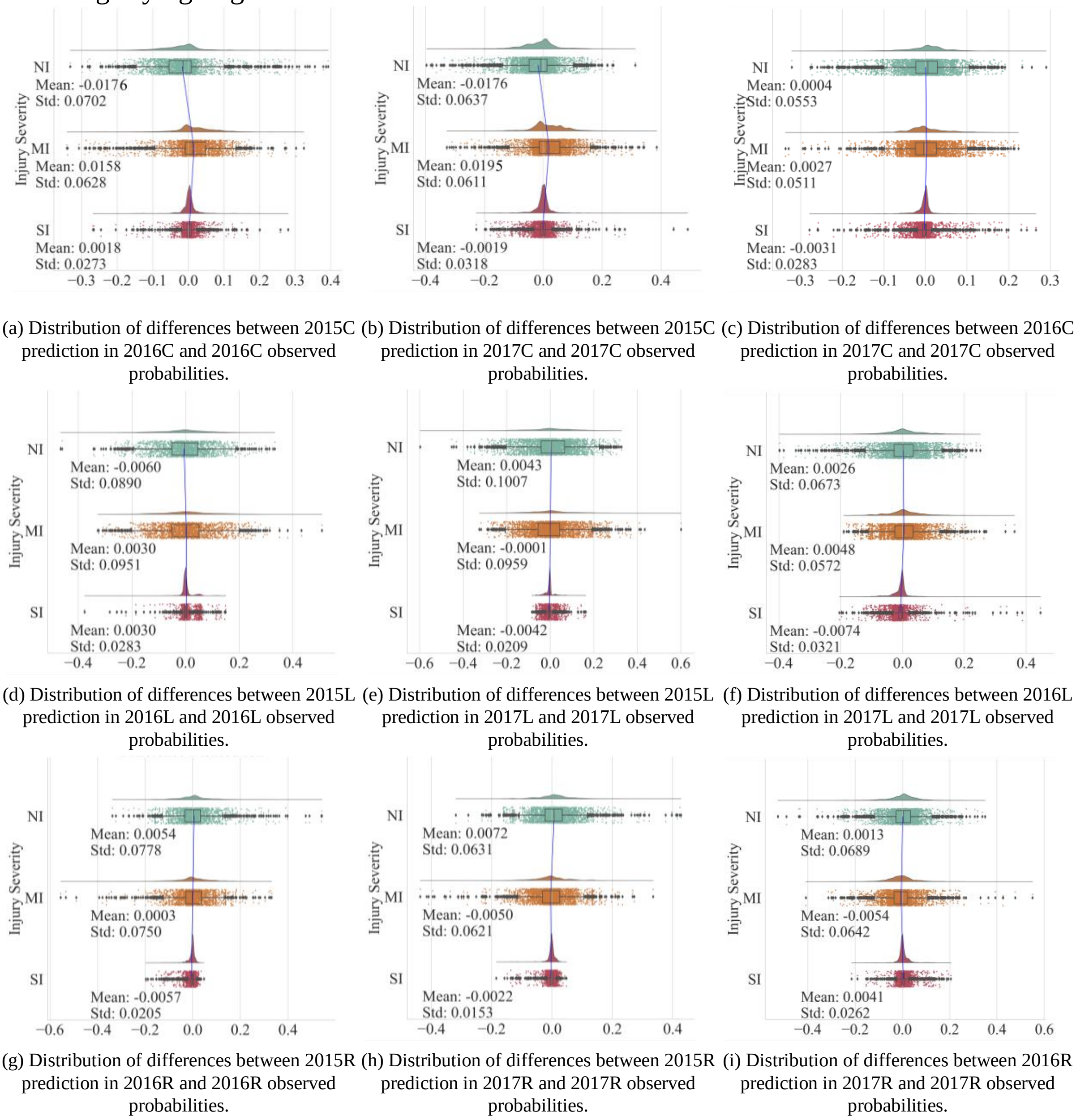
| Observed group | Severity | Predicted group | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Center | | | Left | | | Right | | |
| | | 2015 | 2016 | 2017 | 2015 | 2016 | 2017 | 2015 | 2016 | 2017 |
| Center | NI | - | - | - | –0.0188 | –0.0090 | –0.0048 | –0.0589 | –0.0410 | –0.0362 |
| | MI | - | - | - | 0.0196 | 0.0091 | 0.0090 | 0.0506 | 0.0399 | 0.0296 |
| | SI | - | - | - | –0.0008 | –0.0001 | –0.0042 | 0.0083 | 0.0011 | 0.0066 |
| Left | NI | 0.0317 | 0.0150 | 0.0093 | - | - | - | –0.0409 | –0.0284 | –0.0309 |
| | MI | –0.0329 | –0.0141 | –0.0131 | - | - | - | 0.0338 | 0.0288 | 0.0206 |
| | SI | 0.0012 | –0.0009 | 0.0038 | - | - | - | 0.0071 | –0.0004 | 0.0103 |
| Right | NI | 0.0644 | 0.0469 | 0.0363 | 0.0404 | 0.0302 | 0.0287 | - | - | - |
| | MI | –0.0559 | –0.0457 | –0.0295 | –0.0321 | –0.0312 | –0.0196 | - | - | - |
| | SI | –0.0085 | –0.0012 | –0.0068 | –0.0083 | 0.0010 | –0.0091 | - | - | - |

With respect to temporal shifts, **Table 5** presents the means of probability differences between out-of-sample predictions and within-sample observations over different years. For example, if the 2015 center crash model parameters are used to predict 2016 center crash injury severities, there will be an increase in the probabilities of minor injuries and severe injuries by 0.0158 and 0.0018, while the probability of no injuries will decrease by 0.0176. However, if these parameters are used to predict 2017 center crash injury severities, the probability of no injuries and severe injuries will be underestimated by 0.0176 and 0.0019, while the probabilities of minor injuries will be overestimated by 0.0195. Similarly, both the means of probability differences between the within-sample and out-of-sample predictions for left-side and right-side crashes show an unstable trend, indicating the necessity to account for the temporal instability in forecasting the driver injury severity of single-vehicle crashes (Alogaili and Mannering, 2022; Mannering, 2018).

Regarding the non-transferability of vehicle impact locations, **Table 6** provides the means of probability differences in predicting the driver injury severity across different impact location groups. Likewise, it can be found that the observed probabilities will be overestimated or underestimated in all location-to-location comparisons. However, it is important to note that almost identical directions of differences within the specific injury category are captured across different years. For instance, using the parameters of center crash model in 2015 to predict the left-side crash injury severity will underestimate no injuries and severe injuries, whereas using the same parameters to forecast the minor injury of left-side crashes will overestimate the probability. This finding is also applicable to the years 2016 and 2017 in the context of the same driver injury severity levels, excluding the cases of 2016 left-to-center, 2016 left-to-right, and 2016 right-to-left combinations. Nevertheless, there are variations in the magnitudes of probability differences across different years, which further indicates the temporal instability and non-transferability of the impact location. Another insight from the out-of-sample predictions is that the parameters of center crash models would underestimate the probability of severe injuries in left-side accidents across all periods, while using the same parameters to predict the severe injury of right-side crashes will overestimate the probability. Likewise, utilizing the left-side crash model parameters will result in an overestimation of the likelihood of severe injuries in right-side and center crashes, with slight variations in cases of 2016 left-to-center and 2016 left-to-right predictions. This conversion rule also generally applies to results predicted by the right-side crash models. Consequently, the net effects of aggregate year-to-year and location-to-location shifts are successfully quantified through probability differences between out-of-sample predictions and within-sample observations. This consistent finding also highlights the necessity to make more efforts in mitigating driver injury severities for left-side and center accidents.

To further characterize the net effect, **Fig. 2** shows the detailed distribution of differences between predicted probabilities and observed probabilities concerning three driver injury severity outcomes over different years. The mean differences of each injury-severity category are connected by the blue line in each pairwise comparison subplot. The deviation of each line from the vertical line at 0 provides an intuitive understanding of the aggregate differences in predictions. For example, it could be observed that the overall out-of-sample prediction biases between different years in the center crash models are greater than the prediction differences in the left-side and right-side models. Meanwhile, the kernel density plots of severity prediction differences in each paired comparison subplot can quantify the magnitude of the dispersion. For instance, the dispersion of the probability differences in forecasting injury severities for 2017C using the 2015C model is greater than that of the probability differences in predicting injury severities for 2017L using the 2015L model, as shown in **Fig. 2 (a) and 2 (e)**.

To depict the distribution features of the net effect between different years more accurately, **Table 7** further tabulates the skewness and kurtosis of these probability differences. Specifically, skewness measures the degree of asymmetry in the distribution of data. A negative skewness indicates a left-skewed distribution, a positive skewness indicates a right-skewed distribution, and a skewness of 0 indicates a symmetric distribution. Kurtosis measures the degree of peakedness and thickness of the tails in a data distribution. A positive kurtosis suggests a distribution that is more peaked and has thicker tails than a normal distribution, while a negative kurtosis indicates a distribution that is flatter than a normal distribution. These two indices, representing the differences in out-of-sample predictions for each year's samples, are annotated with different colors to indicate their positive or negative values, with darker colors signifying larger values.




(a) Distribution of differences between 2015C prediction in 2016C and 2016C observed probabilities.

(b) Distribution of differences between 2015C prediction in 2017C and 2017C observed probabilities.

(c) Distribution of differences between 2016C prediction in 2017C and 2017C observed probabilities.

(d) Distribution of differences between 2015L prediction in 2016L and 2016L observed probabilities.

(e) Distribution of differences between 2015L prediction in 2017L and 2017L observed probabilities.

(f) Distribution of differences between 2016L prediction in 2017L and 2017L observed probabilities.

(g) Distribution of differences between 2015R prediction in 2016R and 2016R observed probabilities.

(h) Distribution of differences between 2015R prediction in 2017R and 2017R observed probabilities.

(i) Distribution of differences between 2016R prediction in 2017R and 2017R observed probabilities.

**Fig. 2.** Distribution of differences between predicted probabilities and observed probabilities over different years.

It can be seen that the probability differences in using the 2015 center and left models to predict no injury outcome for the corresponding positions in 2016 and 2017 are left-skewed, while the probability differences in using the 2015 right crash model to predict no injury outcomes for the corresponding positions in 2016 and 2017 are right-skewed. Moreover, the magnitude of the right-skewed values is greater than that of the left-skewed values, further indicating the non-transferability of the collision location parameters. Additionally, a nearly opposite direction of skewness is observed in predicting no injuries and severe injuries between different years, and the magnitude of skewness values in no injuries are generally greater than the corresponding probability differences for severe injuries. This suggests that there are significant differences between the out-of-sample prediction results for different severity levels due to the imbalanced dataset. As for the kurtosis, it is found that the kurtosis of minor injuries is comparable to that of no injuries among all the year-to-year prediction differences, whereas the kurtosis of the prediction differences in severe injuries is significantly greater than those of the previous two, indicating that there is a greater degree of peakedness and thickness in the tails of the distribution of the prediction differences for severe injuries.

Similarly, **Figs. 3–5** depict the detailed distribution of differences between predicted probabilities and observed probabilities regarding three driver injury severity outcomes over different impact locations for three years. **Table 8** also presents the skewness and kurtosis of these probability differences. Apart from the findings that are similar to those presented earlier, it can be seen from blue mean curves that the prediction differences between different positions in the same year are markedly larger than the out-of-sample prediction bias for the same impact location across different years, in comparison to **Fig. 2**. This implies that the non-transferability of the collision location has a greater impact on the prediction than the temporal instability. Meanwhile, it is noteworthy that the out-of-sample prediction differences of each injury severity outcome across different impact positions in 2015 are generally larger than the prediction differences in the other two years. These findings further highlight the importance of considering both temporal instability and location non-transferability in the driver injury severity analysis as both have significant impacts on the accuracy of severity predictions.

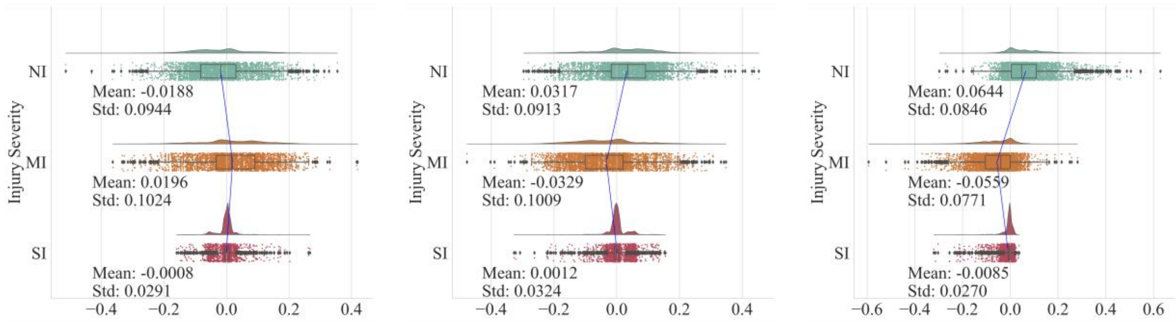
To further quantify the impact of changes in mean differences on the performance of out-of-sample prediction models, the out-of-sample predictive accuracy is also compared to the within-sample observation accuracy. **Fig. 6** illustrates the disparity in out-of-sample prediction accuracy and within-sample observation accuracy between groups within the same collision location but in different years. It can be seen that the majority of accuracy differences predominantly display negative values, indicating a reasonable decrease in overall prediction accuracy. In terms of numerical values, the largest prediction difference is found in the severe injury level, followed by minor injuries and no injuries. However, there are slight discrepancies in the prediction results across different impact locations. Specifically, there is an observed increment in the prediction accuracy for minor injuries in center crashes, concomitant with an increase in the prediction accuracy for no injuries in right-side crashes. By contrast, the prediction accuracy of left-side accidents decreases for all severity levels. These variations imply the existence of divergent temporal effects across impact locations, which can be influenced by factors such as location-specific characteristics and temporal changes in injury patterns. **Fig. 7** showcases the contrasts in out-of-sample prediction accuracy and within-sample observation accuracy between groups in the same year but in a different collision location. The prediction differences show both positive and negative values, which is different from the consistent decrease in accuracy observed in **Fig. 6**. It is worth noting that the direction of the prediction differences is almost consistent with the means of probability differences reported in **Table 6** for predicting injury severity between different impact location groups, whereas this phenomenon is not observed in the analysis of accuracy differences over different years. This notable discrepancy may be attributed to the substantial variations in probability differences across three impact locations. The finding carries significant implications for comprehending the influence of collision location changes on the precision of prediction models pertaining to various levels of the driver injury severity.

**Table 7.** Frequency distribution characteristics of probability differences in predicting the injury severity between different years.

| Observed year | Severity | Predicted year | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 2016 | | | | | | 2017 | | | | | |
| | | Center | | Left | | Right | | Center | | Left | | Right | |
| | | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis |
| 2015 | NI | −0.9824 | 5.2927 | −0.2689 | 1.4660 | 1.0988 | 6.3233 | −0.7243 | 4.3558 | −0.4073 | 1.3764 | 0.7600 | 6.0304 |
| | MI | 0.7489 | 4.7537 | 0.2141 | 1.3494 | −0.8853 | 6.8081 | 0.0860 | 4.1783 | 0.4325 | 1.4765 | −0.6152 | 6.0172 |
| | SI | −1.0883 | 32.1429 | −2.4676 | 38.6673 | −4.0466 | 23.1214 | 1.6661 | 37.0251 | 1.4614 | 10.9905 | −4.8028 | 36.9795 |
| 2016 | NI | - | - | - | - | - | - | −0.7235 | 3.4619 | −0.6134 | 3.4807 | −0.6689 | 6.0578 |
| | MI | - | - | - | - | - | - | 0.0481 | 3.8709 | 0.4686 | 2.3652 | 0.6924 | 7.5888 |
| | SI | - | - | - | - | - | - | −0.1239 | 23.6252 | 2.9124 | 42.4957 | 1.0837 | 16.5791 |

**Table 8.** Frequency distribution characteristics of probability differences in predicting the injury severity between different impact location groups.

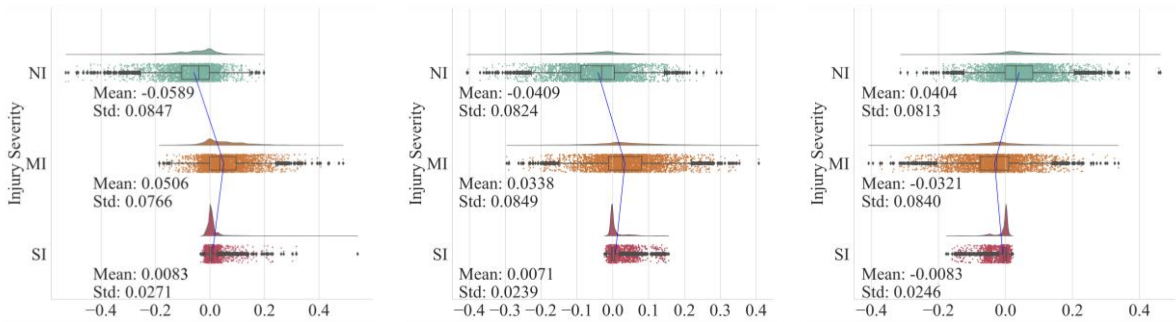
| Observed year | Severity | Predicted year | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Center | | | | | | Left | | | | | | Right | | | | | |
| | | 2015 | | 2016 | | 2017 | | 2015 | | 2016 | | 2017 | | 2015 | | 2016 | | 2017 | |
| | | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis | Skewness | Kurtosis |
| Center | NI | - | - | - | - | - | - | 0.1839 | 0.6443 | −1.0662 | 4.9354 | −1.5818 | 6.2768 | −1.2730 | 3.0330 | −0.7224 | 1.4619 | −2.2076 | 9.1958 |
| | MI | - | - | - | - | - | - | −0.2333 | 0.2055 | 0.8498 | 3.1926 | 1.5407 | 7.6349 | 0.9494 | 1.9338 | 0.4679 | 1.5879 | 1.2703 | 10.3441 |
| | SI | - | - | - | - | - | - | 0.6982 | 14.1082 | −0.3144 | 68.2955 | 3.1685 | 34.5727 | 6.5012 | 72.1255 | 4.1671 | 41.3463 | 4.5506 | 33.0885 |
| Left | NI | −0.1819 | 0.7377 | 1.2433 | 3.8167 | 1.7416 | 5.6175 | - | - | - | - | - | - | −0.3365 | 1.1180 | −0.1543 | 3.5299 | 0.6171 | 4.8153 |
| | MI | 0.2602 | 0.2302 | −1.1182 | 3.2991 | −1.4004 | 5.5862 | - | - | - | - | - | - | 0.1558 | 1.1271 | −0.6132 | 6.3740 | −1.4806 | 8.9486 |
| | SI | −1.5468 | 16.7142 | −0.6554 | 53.8579 | −3.2231 | 25.5707 | - | - | - | - | - | - | 3.2337 | 12.0266 | 7.1003 | 91.6221 | 1.5079 | 9.3259 |
| Right | NI | 1.2129 | 2.9782 | 0.7287 | 1.1168 | 1.9853 | 7.6009 | 0.3542 | 1.5519 | 0.0231 | 3.4325 | −0.3654 | 4.1431 | - | - | - | - | - | - |
| | MI | −0.8945 | 2.0921 | −0.5430 | 1.0752 | −1.0142 | 8.1493 | −0.0873 | 1.3930 | 0.9309 | 8.3671 | 1.3839 | 8.3683 | - | - | - | - | - | - |
| | SI | −4.8706 | 33.2350 | −4.3485 | 31.3375 | −4.1148 | 27.3005 | −3.0844 | 11.1450 | −6.8693 | 86.9108 | −1.6662 | 9.6826 | - | - | - | - | - | - |




(a) Distribution of differences between 2015C prediction in 2015L and 2015L observed probabilities.

(b) Distribution of differences between 2015L prediction in 2015C and 2015C observed probabilities.

(c) Distribution of differences between 2015R prediction in 2015C and 2015C observed probabilities.

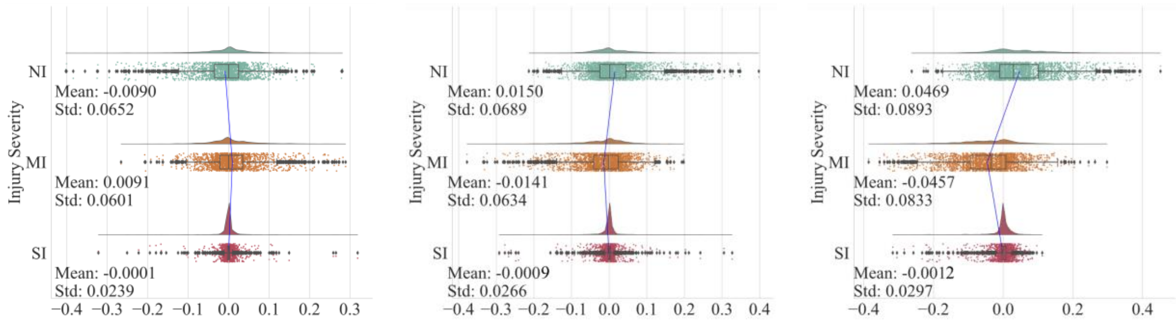



(d) Distribution of differences between 2015C prediction in 2015R and 2015R observed probabilities.

(e) Distribution of differences between 2015L prediction in 2015R and 2015R observed probabilities.

(f) Distribution of differences between 2015R prediction in 2015L and 2015L observed probabilities.

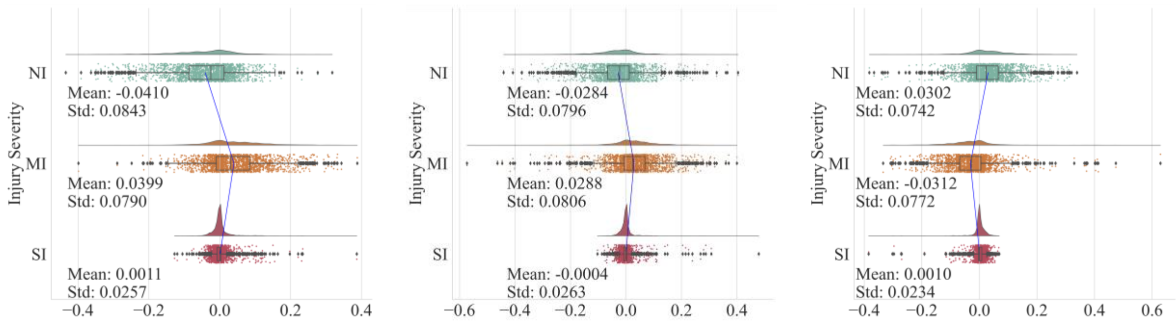
**Fig. 3.** Distribution of differences between predicted probabilities and observed probabilities over groups in 2015.




(a) Distribution of differences between 2016C prediction in 2016L and 2016L observed probabilities.

(b) Distribution of differences between 2016L prediction in 2016C and 2016C observed probabilities.

(c) Distribution of differences between 2016R prediction in 2016C and 2016C observed probabilities.

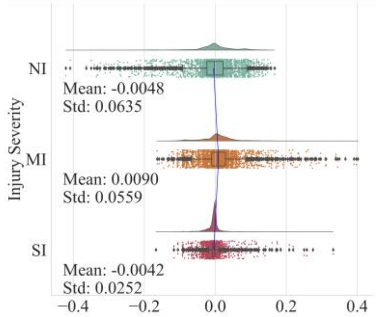



(d) Distribution of differences between 2016C prediction in 2016R and 2016R observed probabilities.

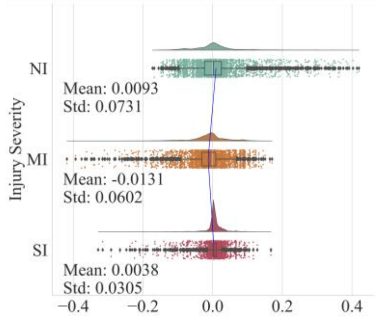
(e) Distribution of differences between 2016L prediction in 2016R and 2016R observed probabilities.

(f) Distribution of differences between 2016R prediction in 2016L and 2016L observed probabilities.

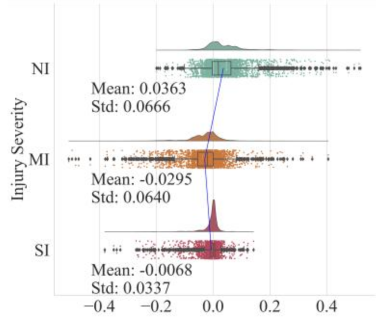
**Fig. 4.** Distribution of differences between predicted probabilities and observed probabilities over groups in 2016.



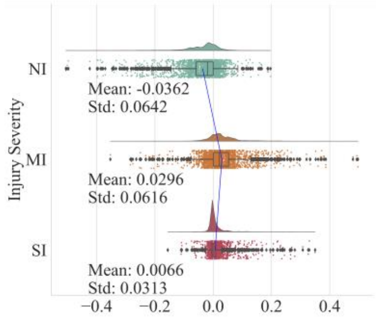

(a) Distribution of differences between 2017C prediction in 2017L and 2017L observed probabilities.



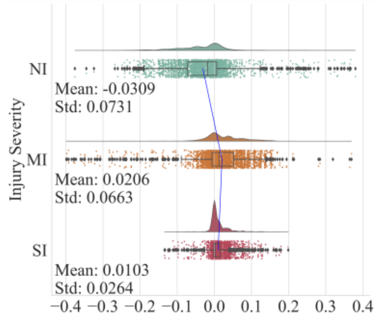

(b) Distribution of differences between 2017L prediction in 2017C and 2017C observed probabilities.



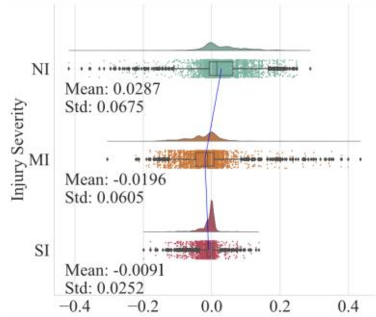

(c) Distribution of differences between 2017R prediction in 2017C and 2017C observed probabilities.




(d) Distribution of differences between 2017C prediction in 2017R and 2017R observed probabilities.




(e) Distribution of differences between 2017L prediction in 2017R and 2017R observed probabilities.




(f) Distribution of differences between 2017R prediction in 2017L and 2017L observed probabilities.

**Fig. 5.** Distribution of differences between predicted probabilities and observed probabilities over groups in 2017.

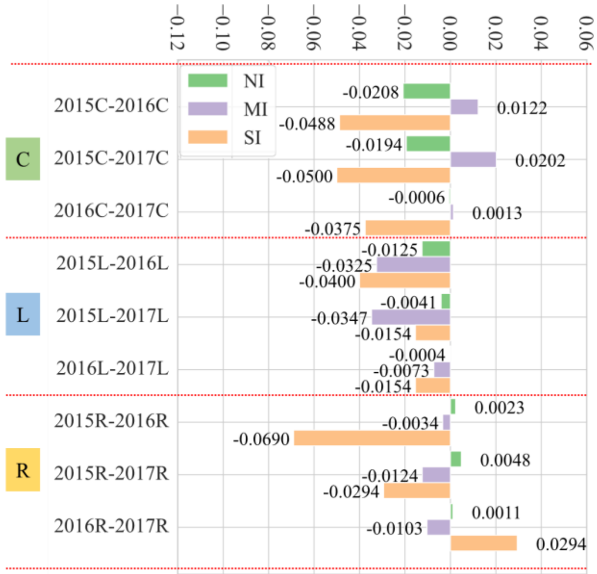



**Fig. 6.** Differences between predicted accuracy and observed accuracy over different years.

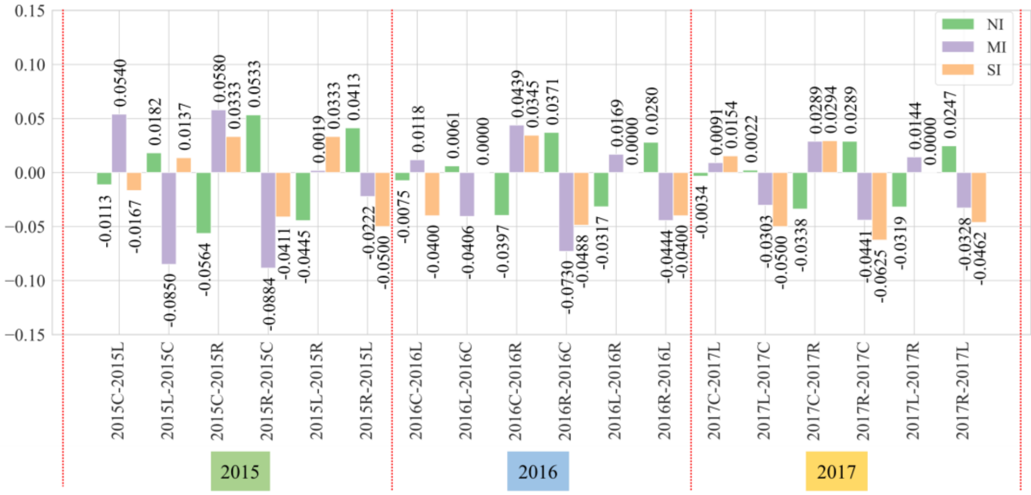



**Fig. 7.** Differences between predicted accuracy and observed accuracy over different impact location groups.

## 6. Results and discussion

**Table 9** presents a comparative analysis of four competitive models, namely the fixed parameters multinomial logit model (MNL), the random parameters multinomial logit model (RPL), the random parameters multinomial logit model with the heterogeneity in the means (RPLM), and the random parameters multinomial logit model with the heterogeneity in the means and variances (RPLMV). The specifications of all models were confirmed through a series of likelihood ratio tests to ensure that the included variables and parameters could significantly improve the converged log-likelihood (Washington et al., 2020). To evaluate these models' performance, four different criteria were used: log-likelihood value, $\rho^2$ value, Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). Specifically, the log-likelihood value serves as a measure of how accurately the model describes the observed data. A higher log-likelihood value indicates a better fit between the model and the data. The $\rho^2$ quantifies the proportion of variance explained by the model, with a higher value signifying a better fit as well. The AIC and BIC are measures of model complexity, with lower values indicating a better tradeoff between model fit and complexity (Akaike, 1974; Schwarz, 1978). The comparative analysis reveals that the random parameters model with the heterogeneity in the means (and variances) outperforms the other models in terms of these four criteria (except for the 2016 center crash model where the heterogeneity in the means and variances is not captured). This model has the highest log-likelihood and $\rho^2$ values, indicating a better fit to the crash data. Meanwhile, the AIC and BIC scores for this model are competitive. Additionally, a series of likelihood ratio tests were employed to compare the random parameters model with heterogeneity in means (and variances) to the other models (Fountas and Anastasopoulos, 2018). The results illustrate that the null hypothesis that the random parameters model with the heterogeneity in the means (and variances) is the same as its counterparts can be rejected at the 95 % confidence level. Therefore, the discussion in this study is based on these superior models.

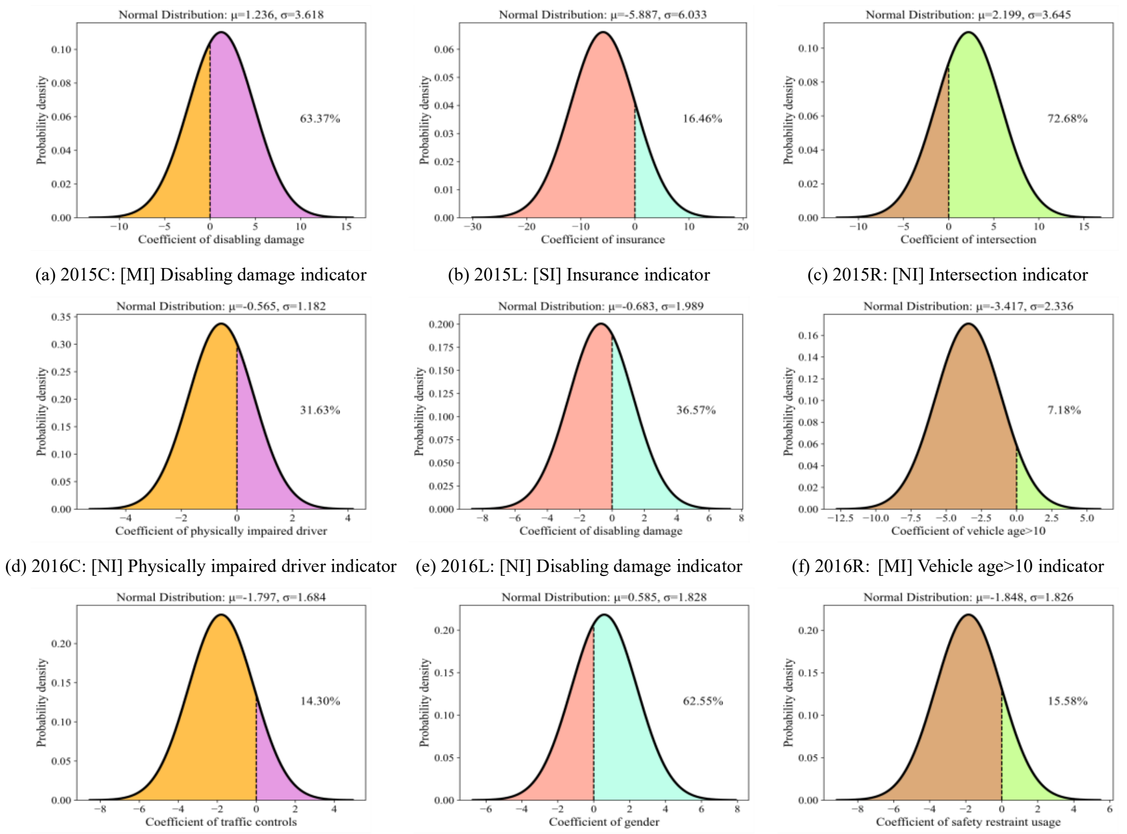
The estimates of random parameters logit models with the heterogeneity in the means (and variances) across different impact locations in three years are presented in **Tables 10–12**, which indicate an overall satisfactory statistical fit with $\rho^2$ values ranging from 0.550 to 0.644. Notably, although the heterogeneity in the means of random parameters was consistently significant (except for the 2016 center crash model), the heterogeneity in the variances was not

**Table 9.** Comparison results of four competitive models (MNL: multinomial logit model, RPL: random parameters multinomial logit model, RPLM: random parameters multinomial logit model with the heterogeneity in the means, RPLMV: random parameters multinomial logit model with the heterogeneity in the means and variances).

| | **2015** | | | | **2016** | | | **2017** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **MNL** | **RPL** | **RPLM** | **RPLMV** | **MNL** | **RPL** | **RPLM** | **MNL** | **RPL** | **RPLM** |
| **Center crashes** | | | | | | | | | | |
| K (Number of parameters) | 17 | 18 | 19 | 20 | 19 | 20 | - | 17 | 18 | 19 |
| Log-likelihood at zero (LL(0)) | –4832.795 | –4832.795 | –4832.795 | –4832.795 | –2749.827 | –2749.827 | - | –4533.973 | –4533.973 | –4533.973 |
| Converged log-likelihood (LL(β)) | –2178.458 | –2169.249 | –2167.216 | –2160.907 | –1235.320 | –1226.689 | - | –2055.221 | –2044.768 | –2042.455 |
| $\rho^2 = 1 - LL(\beta)/LL(0)$ | 0.5492 | 0.5511 | 0.5516 | 0.5529 | 0.5508 | 0.5539 | - | 0.5467 | 0.5490 | 0.5495 |
| AIC | 4390.9 | 4374.5 | 4372.4 | 4361.8 | 2492.6 | 2493.4 | - | 4144.4 | 4125.5 | 4122.9 |
| BIC | 4499.5 | 4489.5 | 4493.8 | 4489.6 | 2603.3 | 2609.9 | - | 4252.0 | 4239.4 | 4243.1 |
| Likelihood ratio test | **MNL vs RPLMV**<br>35.102 (3)<br>[>99.99%] | **RPL vs RPLMV**<br>16.684 (2)<br>[99.98%] | **RPLM vs RPLMV**<br>12.617 (1)<br>[99.96%] | | **MNL vs RPL**<br>17.262 (1)<br>[>99.99%] | | | **MNL vs RPLM**<br>25.533 (2)<br>[>99.99%] | **RPL vs RPLM**<br>4.627 (1)<br>[96.85%] | |
| **Left–side crashes** | | | | | | | | | | |
| K (Number of parameters) | 18 | 19 | 20 | 21 | 16 | 17 | 18 | 18 | 19 | 22 |
| Log–likelihood at zero (LL(0)) | –4160.445 | –4160.445 | –4160.445 | –4160.445 | –2162.069 | –2162.069 | –2162.069 | –3614.434 | –3614.434 | –3614.434 |
| Converged log–likelihood (LL(β)) | –1821.187 | –1819.024 | –1814.100 | –1804.044 | –921.197 | –917.155 | –913.491 | –1565.234 | –1562.377 | –1552.717 |
| $\rho^2 = 1 - LL(\beta)/LL(0)$ | 0.5623 | 0.5628 | 0.5640 | 0.5664 | 0.5739 | 0.5758 | 0.5775 | 0.5669 | 0.5677 | 0.5704 |
| AIC | 3678.4 | 3676.0 | 3668.2 | 3650.1 | 1866.4 | 1864.3 | 1863.0 | 3166.5 | 3162.8 | 3149.4 |
| BIC | 3790.7 | 3794.6 | 3793.0 | 3781.1 | 1955.8 | 1959.3 | 1963.5 | 3276.2 | 3278.6 | 3283.6 |
| Likelihood ratio test | **MNL vs RPLMV**<br>34.285 (3)<br>[>99.99%] | **RPL vs RPLMV**<br>29.960 (2)<br>[>99.99%] | **RPLM vs RPLMV**<br>20.113 (1)<br>[>99.99%] | | **MNL vs RPLM**<br>15.412 (2)<br>[99.95%] | **RPL vs RPLM**<br>7.328 (1)<br>[99.32%] | **RPLM vs RPLM** | **MNL vs RPLM**<br>25.034 (4)<br>[>99.99%] | **RPL vs RPLM**<br>19.320 (3)<br>[99.98%] | |
| **Right–side crashes** | | | | | | | | | | |
| K (Number of parameters) | 17 | 18 | 19 | 21 | 15 | 16 | 17 | 18 | 19 | 20 |
| Log–likelihood at zero (LL(0)) | –4204.389 | –4204.389 | –4204.389 | –4204.389 | –2264.240 | –2264.240 | –2264.240 | –3527.644 | –3527.644 | –3527.644 |
| Converged log–likelihood (LL(β)) | –1506.977 | –1504.443 | –1501.249 | –1497.669 | –877.448 | –874.578 | –869.450 | –1367.873 | –1365.666 | –1358.826 |
| $\rho^2 = 1 - LL(\beta)/LL(0)$ | 0.6416 | 0.6422 | 0.6429 | 0.6438 | 0.6125 | 0.6137 | 0.6160 | 0.6122 | 0.6129 | 0.6148 |
| AIC | 3048.0 | 3044.9 | 3038.5 | 3037.3 | 1784.9 | 1781.2 | 1772.9 | 2771.7 | 2769.3 | 2757.7 |
| BIC | 3154.2 | 3157.4 | 3157.2 | 3168.6 | 1869.4 | 1871.3 | 1868.6 | 2881.1 | 2884.7 | 2879.1 |
| Likelihood ratio test | **MNL vs RPLMV**<br>18.617 (4)<br>[99.91%] | **RPL vs RPLMV**<br>13.548 (3)<br>[99.64%] | **RPLM vs RPLMV**<br>7.161 (2)<br>[97.21%] | | **MNL vs RPLM**<br>15.997 (2)<br>[99.97%] | **RPL vs RPLM**<br>10.257 (1)<br>[99.86%] | | **MNL vs RPLM**<br>18.094 (2)<br>[>99.99%] | **RPL vs RPLM**<br>13.680 (1)<br>[99.98%] | |

found to be statistically significant across three collision locations in years 2016 and 2017. The factors identified to be significant also exhibited discrepancy between the center, left-side, and right-side crash models. **Table 13** shows the marginal effects of the significant variables (arranged by variable classification). The remainder of this section presents a detailed discussion of the estimation results from the variable-level perspective.

### *6.1. Heterogeneity in the means and variances of random parameters*




(a) 2015C: [MI] Disabling damage indicator (b) 2015L: [SI] Insurance indicator (c) 2015R: [NI] Intersection indicator

(d) 2016C: [NI] Physically impaired driver indicator (e) 2016L: [NI] Disabling damage indicator (f) 2016R: [MI] Vehicle age>10 indicator

(g) 2017C: [MI] Traffic controls indicator (h) 2017L: [MI] Gender indicator (i) 2017R: [MI] Safety restraint usage indicator

**Fig. 8**. Distribution of the random parameters.

As indicated in **Table 10**, three variables were identified as random parameters with normal distributions in center crash models: the disabling damage indicator, physically impaired driver indicator, and traffic controls indicator, whereas in left-side crash models, the insurance indicator, disabling damage indicator, as well as gender indicator were identified as significant random parameters, as shown in **Table 11**. Concerning right-side collision models in **Table 12**, it was discovered that the intersection indicator, vehicle age>10 indicator, and safety restraint usage indicator produced random parameters with heterogeneous means or variances. The results demonstrate that a varying influence of the unobserved characteristics on the driver injury severity between different vehicle impact locations is captured by these random parameters (Mannering et al., 2020). **Fig. 8** presents the probability density diagrams of these identified normally distributed random parameters. Taking the 2017 center crash model as an example, the traffic control indicator defined to minor injury outcome produces a random parameter that is normally distributed with a mean of −1.797 and a standard deviation of 1.684. This implies that the parameter of this variable is negative with a probability of 85.70% and positive with a probability of 14.30% for each observation.

As for the heterogeneity in the means, the presence of roadway with more than six lanes was observed to decrease the means of heterogeneity in the disabling damage indicator for minor injury outcomes in the 2015 center crash model, whereas the insurance indicator would increase the mean of the random parameter generated by the traffic controls indicator specific to minor injuries in 2017 center crashes. It is worth noting that no explanatory variable was found to have significant influences on the heterogeneity in the means of physically impaired driver indicator defined to no injuries in the 2016 center crash model. Turning to the heterogeneity in the means of left-side crash models, the physically impaired driver indicator was observed to decrease the mean of its random parameter, resulting in a decreased likelihood of no injuries in 2016. On the other hand, this indicator would elevate the mean of the insurance indicator in the 2015 left-side crash model, thereby increasing the possibility of severe injury outcomes. In the presence of 4–6 lanes and animals, the mean of female drivers for minor injury would decrease in 2017 left-side crashes, making minor injury less likely. By contrast, when the first harmful event was identified as the non-colliding object such as a rollover, there was an observed increment in the mean, consequently amplifying the likelihood of minor injuries. Different from the 2017 left-side crash model, the female driver indicator was found to be a significant variable that increased the means of heterogeneity in the vehicle age older than 10 years indicator for minor injury outcomes in the 2016 right-side crash model. Regarding the 2015 right-side crash model, the mean of intersection indicator defined to no injury would increase when the traffic control was functioning. In the 2017 right-side crash model, middle-aged drivers were found to be associated with increased mean of the safety restraint usage indicator, making minor injuries more likely.

With regard to the heterogeneity in the variances, none of explanatory variables had significant impacts on the variances of the random parameters across all 2016 and 2017 crash models, as shown in **Tables 10–12**. The insured vehicle indicator was found to statistically decrease the variance of the random parameter produced by the disabling damage indicator for minor injury in 2015 center crashes, leading to more observations decreasing the likelihood of minor injury. Turning to the 2015 left-side crash model, the variances of insurance indicator specific to severe injury would decline if safety restraints were utilized by drivers in these single-vehicle accidents. Regarding right-side crashes in 2015, it was observed that the disabling damage led to an increase in the variance of the random parameters relating to the intersection indicator for no injury, while insured vehicles exhibited a significant association with decreased variance.

### *6.2. Crash characteristics*

The collision with fixed object indicator consistently resulted in more severe injuries (with positive marginal effects for minor injuries or severe injuries) in 2015 and 2017. It can be speculated that the tire-road friction coefficient under adverse road conditions is smaller than that of dry surfaces, thus limiting the effectiveness of braking systems in hazardous situations. Consequently, there is greater kinetic energy dissipation during a collision with fixed objects, thereby increasing the likelihood of fatal and minor injuries (Roque et al., 2015). Regarding the non-collision indicator, it was also observed to be associated with an increased possibility of more severe injury for each location in one or two years, further reflecting the potential temporal stability and transferability of this indicator. This could be attributed to the inherent seriousness of this crash type, that is, non-collision accidents such as overturns are typically associated with strong lateral impact, thus resulting in injuries and fatalities (Yan et al., 2022). Nevertheless, considerable variations in the combination of different damage locations and years were captured, indicating the complexity of interaction mechanism. It is also noteworthy that although the estimated parameter of the animal-involved collision indicator consistently led to less severe injury (with positive values for no injury and negative values for minor injury or severe injury) across three observed years, this indicator was found to be significant in all center crash models but only significant in one or two side-wipe crash models, demonstrating the slight diversity across impact locations.

The non-functional damage indicator was identified as a determinant to be negatively associated with the occurrence of minor injuries or severe injuries in 2017 center and right-side crash models, while the functional damage indicator was statistically significant in all models except for the 2016 right-side crash model. Furthermore, it was observed that the disabling damage indicator had a significant impact on the severity of crashes across all combinations of years and locations. Notably, this indicator consistently correlated with more severe driver injuries (with positive values indicating minor or severe injuries). These findings suggest that the disabling damage indicator is not only consistent over time but also transferable across different crash locations. The results were intuitive since the driver injury severity and the vehicle damage severity were positively related when crashes happened. With respect to indicators reflecting the movement type preceding the crashes, the straight driving indicator would increase the possibility of more severe injury in 2016 center and 2017 left-side crash models, whereas these indicators were found to be statistically insignificant in right-side crash models. This interesting phenomenon can be explained by the fact that drivers typically bear indirect damage in left-hand drive vehicles when right-side crashes happen, thus sharing lower risks and being less sensitive to this movement indicator compared to collisions occurring in the other two impact positions.

### *6.3. Driver characteristics*

For age-related indicators, it was observed that young and middle-aged drivers were associated with a decreased probability of severe injuries in 2017 crash models. However, these two variables were not found to be significant in 2015 and 2016 models. In contrast, the old driver indicator was observed to maintain a positive relationship with more severe injury crashes. Besides, it is noteworthy that this variable was identified as a rather consistent characteristic among three impact locations from 2015 to 2017. These findings are in line with previous studies (Alnawmasi and Mannering, 2022b; Chen et al., 2016). A possible explanation is that the declined perception and reaction ability of old drivers would cause serious obstacles in dealing with complicated traffic environments and subsequently lead to more serious injuries.

The safety restraint usage indicator was also found to be temporally and positionally stable across different collision locations, making minor or severe injuries less likely. Previous findings also found that using protection such as the belt or helmet can significantly decrease injury severities in traffic accidents (Wang and Abdel-Aty, 2008; Li et al., 2019). The results suggested that stricter regulations should be formulated to increase the proportion of drivers with seatbelts on. With respect to drivers' gender attributes, female drivers consistently demonstrated temporal stability and location transferability throughout the observed year, with a positive effect on minor or severe injuries due to their susceptibility to traffic accidents (Alnawmasi and Mannering, 2022).

Regarding the physically impaired indicators, the marginal effects showed that impaired drivers tended to increase the possibility of minor or severe injuries (Behnood and Mannering, 2017). Compared to left-side and right-side crashes, severe injury crashes might be more likely to occur in center crashes when the driver was in the physically impaired condition. Empirical studies have shown that drivers' driving skills, including attention, scanning, and information processing ability, would deteriorate even at low blood alcohol concentration levels (European Commission, 2018; Yan et al., 2021a). Therefore, the joint effect of the diminished capacity to avoid risks in case of danger and more aggressive driving behaviors such as speeding would result in more severe injuries, especially in head-on collisions with the fastest energy decay rate under adverse road surface conditions.

### *6.4. Temporal characteristics*

The season-of-year indicators generally yielded respective consistent marginal effects across different impact locations over the years. Regarding the marginal effects of the spring indicator, minor or severe injuries were more likely to occur in the variable-significant models over three different impact locations. The summer indicator was also found to be positively associated with a decreased possibility of no injuries while making minor injuries more likely. By contrast, it was observed that the autumn would result in less likelihood of severe injury in 2015 left-side crashes. The possible reason underlying such divergency is that adverse weather conditions (e.g., typhoons and rainstorms) that typically occur in spring and summer can significantly deteriorate the driving environment (Wang et al., 2022), whereas the autumn indicator is generally associated with fine weather with low precipitation, adequate sunlight, and comfortable temperature in Ohio (Weather Atlas, 2022).

The early morning indicator was only statistically significant in 2015 and 2017 right-side crash models, which demonstrated positive marginal effects in relation to minor or severe injuries. This phenomenon can be explained from two perspectives. On the one hand, major causes of catastrophic collisions, such as speeding, fatigue, and drowsy driving, are more prevalent in the early morning hours (Siebert et al., 2019). Another alternative explanation might be the reduced visibility during early morning periods (Yan et al., 2021b), which significantly increased risks of right-side crashes compared to left-side and center collisions on adverse road surfaces. Note that only the 2016 left-side crash model captured the negative effect of the afternoon indicator, which is associated with the increased likelihood of minor injuries and severe injuries. Apart from the similar issues of distracted and fatigued driving in the early morning, afternoons usually witness high traffic volumes during rush hours. The increased number of vehicles can result in road congestion and traffic jams, subsequently raising the probability of accidents. Compared to weekends, the weekday indicator was observed to make severe injuries less likely among 2016 left-side crashes, which aligns with previous empirical findings (Yan et al., 2021a; Behnood and Al-Bdairi, 2020).

### *6.5. Vehicle characteristics*

The passenger car involvement indicator was identified as a significant determinant only in the 2015 left-side and 2016 center crash models with a higher possibility of no injuries, while it was not identified as a significant variable in right-side accidents. Compared to trucks and SUVs, passenger cars equipped with specialized safety features, such as advanced airbag systems, crumple zones, and side impact beams, are more effective in mitigating impact forces and reducing the risk of injuries, especially in destructive left-side and center crashes. Being the insured vehicle was found to significantly influence driver injury severities across various combinations of different impact locations and years under poor road surface conditions, demonstrating a high level of temporal consistency and impact location transferability. It was found to be stably associated with a decreased probability of more severe injury since most insured drivers may have higher safety awareness (Yan et al., 2021a). Distinct findings also revealed that insurance made drivers more likely to sustain more severe injuries (Zhang et al., 2014). This might be caused by the driving-compensating principle that insured drivers were less cautious and more likely to engage in dangerous driving behaviors.

With respect to the vehicle age, the 5–10 years old indicator was observed to be of temporal and positional instability. In the 2016 center crash model, it was found to have a positive impact on severe injuries, whereas it turned out to be negatively related to the incidence of severe injuries in the 2015 right-side crash models. This indicates that, even for well-functioned automobiles, the vehicle's kinetic energy could instantaneously transfer to drivers and result in more severe injuries in center crashes. By contrast, the vehicle's kinetic energy might be distributed between the vehicle and the driver in right-side collisions, thus resulting in less severe injuries. The 0–5 years old indicator was observed to be positively related to severe injury severities in the variable-significant model while producing subtle differences in their marginal effects owing to the divergences of estimated parameter categories. Likewise, when crashes involving more than 10 years older vehicles, the likelihood of severe injuries was observed to increase but only generated statistical significance in the 2016 right-side crash model. It is understandable that vehicles over ten years were typically associated with poor mechanical properties and low stability, which might cause potential safety hazards and result in a higher probability of more severe injury outcomes (Yan et al., 2021a).

### *6.6. Roadway characteristics*

In 2015 right-side and 2017 center crashes, the results showed that there was a lower possibility of more severe injuries if the accident occurred on the road section with traffic controls functioning. This is consistent with previous findings that signal controls implemented at intersections with complex traffic conditions can effectively regulate the traffic flow in orderliness (Wang and Abdel-Aty, 2008). For the number of lanes indicator, it is noteworthy that these variables were all found to be statistically insignificant in right-side crashes and 2016 crashes, indicating the sensitivity and non-transferability to different impact locations and years. It was observed that being 1–3 lane roadways and greater than 6 lane roadways generally produced consistent findings for center and left-side crashes in 2015 and 2017, resulting in more severe outcomes. In contrast, crashes occurred in 4–6 lane roadways would result in less severe injuries for the 2015 left-side combination. One possible reason for this remarkable difference is the relatively narrower driving space on 1–3 lane roadways and the more aggressive driving behaviors of drivers on wider roads (Se et al., 2021).

Regarding the variables reflecting roadway types, the freeway indicator was only found to be statistically significant in the 2016 center crash model, making more severe injury less likely, whereas the municipal street indicator sustained less severe injuries in 2016 left-side crashes. Municipal streets were also found to be negatively associated with minor injuries and severe injuries in right-side crashes (in 2015 and 2016). One rationale lies in the fact that highways and municipal roads typically feature spacious lanes, medians, and effective traffic management systems, which help reduce traffic congestion and the risk of accidents. An alternative reason is that these roads are subject to stringent regulation and enforcement measures. Traffic police and surveillance systems regularly patrol and monitor highways and municipal roads to ensure compliance with traffic rules and speed limits. Besides, it was found that the intersection indicator was positively correlated with the no injury or minor injury outcomes in the 2015 right-side crash model. One possible explanation is that drivers tended to be more cautious with a slower speed when driving near intersections with wet, snowy, or icy road surfaces (Pervaz et al., 2022), thereby decreasing the possibility of severe injuries.

Despite being insignificant in three impact location models of 2016, the speed limit of 30–60 mph showed the potential impact location transferability of corresponding parameter estimates, which was negatively associated with no injuries and positively associated with the minor injuries or severe injuries in 2015 center and left-side collisions, as well as that in 2017 right-side crashes. This is reasonable since the braking distance of vehicles would significantly increase under adverse road conditions. Even within lower speed limits, drivers may still be unable to stop in a timely manner if there are obstacles or other vehicles on the road, resulting in collisions and serious injuries (Li et al., 2018). Furthermore, maintaining vehicle stability can also be challenging in unfavorable surface scenarios, as vehicles are prone to losing balance or experiencing skidding, thereby increasing the risk of rollovers and collisions.

### *6.7. Environment characteristics*

Regarding the environmental attributes, only the dark-unlighted indicator specific to minor injuries and the adverse weather condition indicator specific to no injuries were found to generate significance statistically. The former variable exhibited marginal effects in the 2015 left-side crash model, where it was positively associated with no injuries and severe injuries. However, it was not identified as a significant variable in all center and right-side crash models, demonstrating the diversity across different damage locations. It can be assumed that compared to far-side crashes, near-side accidents were more sensitive to the impact of lighting conditions. Therefore, the lighting condition should be improved to reduce the occurrence of such accidents (Chang et al., 2022). Another insightful understanding is the extreme nature of this variable. Namely, even though drivers tended to compensate for adverse visibility conditions by modifying their driving behaviors to maintain an acceptable level of risk, there was still a higher likelihood of severe injury severities once the crash happened.

Note that the adverse weather condition consistently exhibited a negative correlation to minor and severe injuries in 2016 crashes across all impact locations, whereas it was not identified as a significant variable in 2015 and 2017 crash models. This implies the presence of temporal shifts between disaggregated years, highlighting the importance of considering temporal dynamics when implementing targeted injury prevention strategies. This is consistent with findings of historical empirical studies where drivers were found to behave more carefully under unfavorable driving conditions due to the risk-compensating mindset (Behnood and Mannering, 2019; Islam and Mannering, 2020, 2021; Pang et al., 2022; Wang et al., 2018).

**Table 10.** Model estimation results of random parameters logit models with heterogeneity in the means and variances in center crashes over the years.

| Variable | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|
| | Parameter | t-Stat | Parameter | t-Stat | Parameter | t-Stat |
| [MI] Constant | –3.805 | –8.86 | –1.836 | –6.02 | - | - |
| [SI] Constant | –3.798 | –8.27 | –2.655 | –6.52 | –5.938 | –7.60 |
| **Random parameters (normally distributed)** | | | | | | |
| [MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | 1.236 | 4.97 | - | - | - | - |
| *Standard deviation* | 3.618 | 4.50 | - | - | - | - |
| [MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | - | - | - | - | –1.797 | –3.58 |
| *Standard deviation* | - | - | - | - | 1.684 | 3.90 |
| [NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | - | - | –0.565 | –2.70 | - | - |
| *Standard deviation* | - | - | 1.182 | 1.65 | - | - |
| **Heterogeneity in the means of random parameters** | | | | | | |
| [MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise): The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | –0.927 | –2.33 | - | - | - | - |
| [MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise): Insurance indicator (1 if vehicle was insured, 0 otherwise) | - | - | - | - | 0.504 | 2.31 |
| **Heterogeneity in the variances of random parameters** | | | | | | |
| [MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise): Insurance indicator (1 if vehicle was insured, 0 otherwise) | –0.638 | –3.26 | - | - | - | - |
| **Crash characteristics** | | | | | | |
| [NI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | –1.315 | –4.07 | - | - | - | - |
| [NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | - | - | –0.506 | –1.94 | - | - |
| [NI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | | | 2.199 | 6.50 | 2.080 | 6.84 |
| [MI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | –1.677 | –3.75 | - | - | - | - |
| [NI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise) | - | - | - | - | 2.051 | 6.99 |
| [MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise) | 0.885 | 4.92 | 0.965 | 3.95 | –1.342 | –6.98 |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | - | - | –1.884 | –8.64 | - | - |
| [SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | | | | | 2.696 | 4.48 |
| [NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise) | - | - | –0.281 | –2.25 | - | - |
| **Driver characteristics** | | | | | | |
| [MI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise) | - | - | - | - | 0.263 | 2.09 |
| [NI] Old driver indicator (1 if driver age over 50, 0 otherwise) | –1.005 | –3.70 | –1.067 | –2.88 | –1.109 | –4.23 |
| [MI] Old driver indicator (1 if driver age over 50, 0 otherwise) | –0.630 | –2.14 | –0.691 | –1.85 | –0.785 | –2.72 |
| [NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | 1.853 | 6.67 | 2.635 | 7.25 | 1.570 | 5.52 |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | 0.825 | 2.54 | 1.611 | 4.63 | 0.701 | 2.34 |
| [NI] Gender indicator (1 if driver was female, 0 otherwise) | –0.833 | –7.20 | –0.540 | –4.75 | –0.646 | –5.62 |
| [NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | –1.234 | –7.10 | - | - | –1.260 | –6.69 |
| **Temporal characteristics** | | | | | | |
| [NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | –0.337 | –2.27 | - | - | - | - |
| [MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise) | 0.475 | 2.50 | - | - | - | - |
| **Vehicle characteristics** | | | | | | |
| [SI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise) | - | - | –0.676 | –2.01 | - | - |
| [NI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | - | - | 0.479 | 3.76 | 0.990 | 6.45 |
| [SI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | –1.029 | –4.16 | - | - | - | - |
| [SI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise) | - | - | - | - | 0.646 | 2.40 |

| Variable | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|
| | Parameter | t-Stat | Parameter | t-Stat | Parameter | t-Stat |
| [NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise) | - | - | –0.196 | –1.65 | - | - |
| **Roadway characteristics** | | | | | | |
| [NI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | - | - | - | - | –1.070 | –2.26 |
| [SI] The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise) | - | - | - | - | 0.834 | 3.43 |
| [MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | 1.051 | 3.77 | - | - | - | - |
| [NI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise) | - | - | 0.984 | 2.48 | - | - |
| [MI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise) | - | - | 0.760 | 1.91 | - | - |
| [NI] Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise) | –0.321 | –2.70 | - | - | - | - |
| **Environment characteristics** | | | | | | |
| [NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise) | - | - | 0.216 | 1.77 | - | - |
| **Model statistics** | | | | | | |
| Number of observations (*N*) | 4399 | | 2503 | | 4127 | |
| Number of estimated parameters (*K*) | 20 | | 20 | | 19 | |
| Log-likelihood at zero, $LL(0)$ | –4832.795 | | –2749.827 | | –4533.973 | |
| Log-likelihood at convergence, $LL(\beta)$ | –2160.907 | | –1226.689 | | –2042.455 | |
| $\rho^2 = 1 - LL(\beta)/LL(0)$ | 0.553 | | 0.554 | | 0.550 | |
| Akaike information criterion (AIC) | 4361.8 | | 2493.4 | | 4122.9 | |
| Bayesian Information Criterion (BIC) | 4489.6 | | 2609.9 | | 4243.1 | |

**Table 11.** Model estimation results of random parameters logit models with heterogeneity in the means and variances in left-side crashes over the years.

| Variable | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|
| | Parameter | t-Stat | Parameter | t-Stat | Parameter | t-Stat |
| [MI] Constant | –2.855 | –8.85 | –1.402 | –3.46 | –4.654 | –10.68 |
| [SI] Constant | –7.998 | –7.01 | –2.101 | –3.65 | –6.878 | –10.72 |
| **Random parameters (normally distributed)** | | | | | | |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | - | - | –0.683 | –1.71 | - | - |
| *Standard deviation* | - | - | 1.989 | 2.78 | - | - |
| [SI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | –5.887 | –1.65 | - | - | - | - |
| *Standard deviation* | 6.033 | 2.26 | - | - | - | - |
| [MI] Gender indicator (1 if driver was female, 0 otherwise) | - | - | - | - | 0.585 | 2.21 |
| *Standard deviation* | - | - | - | - | 1.828 | 3.34 |
| **Heterogeneity in the means of random parameters** | | | | | | |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise): Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | - | - | –0.982 | –1.70 | - | - |
| [SI] Insurance indicator (1 if vehicle was insured, 0 otherwise): Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | 2.844 | 2.13 | - | - | - | - |
| [MI] Gender indicator (1 if driver was female, 0 otherwise): Non-collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | - | - | - | - | 1.650 | 1.65 |
| [MI] Gender indicator (1 if driver was female, 0 otherwise): The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise) | - | - | - | - | –0.656 | –2.86 |
| [MI] Gender indicator (1 if driver was female, 0 otherwise): Animal indicator (1 if animal involved in the crash, 0 otherwise) | - | - | - | - | –3.313 | –2.93 |
| **Heterogeneity in the variances of random parameters** | | | | | | |
| [SI] Insurance indicator (1 if vehicle was insured, 0 otherwise): Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | –0.625 | –3.11 | - | - | - | - |
| **Crash characteristics** | | | | | | |
| [NI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | –1.691 | –7.27 | - | - | - | - |
| [MI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | - | - | - | - | 1.540 | 4.44 |

| Variable | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|
| | Parameter | t-Stat | Parameter | t-Stat | Parameter | t-Stat |
| [SI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | | | | | 1.825 | 3.37 |
| [NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | –1.754 | –6.26 | - | - | –1.589 | –4.05 |
| [NI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | - | - | 2.109 | 4.65 | - | - |
| [MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise) | –0.568 | –5.01 | 0.696 | 3.05 | 1.224 | 4.85 |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | - | - | - | - | –2.268 | –9.09 |
| [SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | 3.851 | 3.58 | - | - | - | - |
| [NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise) | - | - | - | - | –0.237 | –1.89 |
| **Driver characteristics** | | | | | | |
| [NI] Young driver indicator (1 if driver age below 30 years, 0 otherwise) | - | - | - | - | 0.318 | 2.57 |
| [NI] Old driver indicator (1 if driver age over 50, 0 otherwise) | - | - | –0.427 | –2.09 | –0.539 | –1.78 |
| [MI] Old driver indicator (1 if driver age over 50, 0 otherwise) | - | - | - | - | –0.661 | –2.09 |
| [SI] Old driver indicator (1 if driver age over 50, 0 otherwise) | 0.934 | 2.40 | - | - | - | - |
| [NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | | | 2.373 | 4.61 | | |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | –0.751 | –4.50 | 1.828 | 3.76 | - | - |
| [NI] Gender indicator (1 if driver was female, 0 otherwise) | | | –0.794 | –4.66 | | |
| [MI] Gender indicator (1 if driver was female, 0 otherwise) | 0.588 | 6.37 | - | - | - | - |
| [NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | - | - | –2.340 | –3.72 | - | - |
| [MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | 0.575 | 3.76 | –1.320 | –2.34 | 0.531 | 2.86 |
| **Temporal characteristics** | | | | | | |
| [SI] Weekday indicator (1 if crash occurred during the weekday, 0 otherwise) | - | - | –0.768 | –1.77 | - | - |
| [NI] Afternoon indicator (1 if time of day is between 12 PM to 6:59 PM, 0 otherwise) | - | - | –0.376 | –2.21 | - | - |
| [MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | 0.373 | 2.89 | - | - | - | - |
| [MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise) | 0.349 | 2.32 | - | - | - | - |
| [MI] Autumn indicator (1 if crash occurred during the autumn, 0 otherwise) | 0.236 | 1.89 | - | - | - | - |
| **Vehicle characteristics** | | | - | - | | |
| [MI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise) | –0.368 | –4.00 | - | - | - | - |
| [NI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | - | - | 0.758 | 3.75 | 1.215 | 4.59 |
| [MI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | - | - | - | - | 0.643 | 2.26 |
| **Roadway characteristics** | | | | | | |
| [SI] The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise) | - | - | - | - | 1.066 | 3.78 |
| [MI] The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise) | 0.221 | 2.13 | - | - | - | - |
| [NI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | - | - | - | - | –1.074 | –2.60 |
| [MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | - | - | - | - | –1.179 | –2.64 |
| [MI] Speed limit 30–60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise) | 0.382 | 3.55 | - | - | - | - |
| [NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise) | - | - | 0.346 | 1.93 | - | - |
| **Environment characteristics** | | | | | | |
| [SI] Dark-lighted indicator (1 if lighting condition is dark-lighted, 0 otherwise) | –0.214 | –1.97 | - | - | - | - |
| [NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise) | - | - | 0.556 | 3.19 | - | - |
| **Model statistics** | | | | | | |
| Number of observations ($N$) | 3787 | | 1968 | | 3290 | |
| Number of estimated parameters ($K$) | 21 | | 18 | | 22 | |
| Log-likelihood at zero, $LL(0)$ | –4160.445 | | –2162.069 | | –3614.434 | |
| Log-likelihood at convergence, $LL(\beta)$ | –1804.044 | | –913.491 | | –1552.717 | |

| Variable | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|
| | Parameter | t-Stat | Parameter | t-Stat | Parameter | t-Stat |
| $\rho^2 = 1 - LL(\beta)/LL(0)$ | 0.566 | | 0.577 | | 0.570 | |
| Akaike information criterion (AIC) | 3650.1 | | 1863.0 | | 3149.4 | |
| Bayesian Information Criterion (BIC) | 3781.1 | | 1963.5 | | 3283.6 | |

**Table 12.** Model estimation results of random parameters logit models with heterogeneity in the means and variances in right-side crashes over the years.

| Variable | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|
| | Parameter | t-Stat | Parameter | t-Stat | Parameter | t-Stat |
| [MI] Constant | –2.371 | –8.36 | –1.172 | –3.67 | –2.322 | –4.10 |
| [SI] Constant | –4.990 | –19.13 | –4.855 | –7.45 | –5.493 | –9.60 |
| **Random parameters (normally distributed)** | | | | | | |
| [MI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise) | - | - | –3.417 | –3.99 | - | - |
| *Standard deviation* | - | - | 2.336 | 3.63 | - | - |
| [NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise) | 2.199 | 1.75 | - | - | - | - |
| *Standard deviation* | 3.645 | 2.30 | - | - | - | - |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | - | - | - | - | –1.848 | –3.72 |
| *Standard deviation* | - | - | - | - | 1.826 | 2.61 |
| **Heterogeneity in the means of random parameters** | | | | | | |
| [NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise): Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | 1.471 | 2.46 | - | - | - | - |
| [MI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise): Gender indicator (1 if driver was female, 0 otherwise) | | | 1.113 | 2.74 | | |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise): Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise) | - | - | - | - | 1.204 | 3.57 |
| **Heterogeneity in the variances of random parameters** | | | | | | |
| [NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise): Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | 0.249 | 1.83 | - | - | - | - |
| [NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise): Insurance indicator (1 if vehicle was insured, 0 otherwise) | –0.317 | –1.85 | - | - | - | - |
| **Crash characteristics** | - | - | - | - | - | - |
| [MI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | - | - | - | - | 1.914 | 3.94 |
| [NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | - | - | –0.685 | –2.30 | - | - |
| [MI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | | | | | 2.062 | 3.52 |
| [NI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | 2.010 | 4.82 | 1.417 | 3.32 | - | - |
| [MI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise) | - | - | - | - | –2.257 | –5.04 |
| [MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise) | 0.552 | 2.82 | - | - | –1.221 | –4.73 |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | –1.558 | –8.89 | –1.391 | –7.45 | - | - |
| [SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | - | - | - | - | 1.270 | 3.20 |
| **Driver characteristics** | | | | | | |
| [NI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise) | - | - | - | - | 1.080 | 3.57 |
| [NI] Old driver indicator (1 if driver age over 50, 0 otherwise) | - | - | - | - | –0.448 | –2.41 |
| [MI] Old driver indicator (1 if driver age over 50, 0 otherwise) | - | - | 0.393 | 1.98 | - | - |
| [NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | - | - | 1.768 | 6.61 | - | - |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | –0.663 | –3.62 | - | - | - | - |
| [NI] Gender indicator (1 if driver was female, 0 otherwise) | - | - | –0.495 | –2.72 | - | - |
| [MI] Gender indicator (1 if driver was female, 0 otherwise) | 0.778 | 6.48 | - | - | 0.870 | 4.41 |

| Variable | 2015 | | 2016 | | 2017 | |
|---|---|---|---|---|---|---|
| | **Parameter** | **t-Stat** | **Parameter** | **t-Stat** | **Parameter** | **t-Stat** |
| [NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | –0.671 | –3.81 | –1.006 | –2.89 | –1.958 | –4.77 |
| [MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | - | - | - | - | –1.262 | –2.79 |
| **Temporal characteristics** | | | | | | |
| [MI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise) | –0.499 | –3.19 | - | - | - | - |
| [SI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise) | - | - | - | - | –1.733 | –2.32 |
| [NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | –0.418 | –2.76 | –0.534 | –2.77 | - | - |
| [MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | - | - | - | - | 0.570 | 2.79 |
| [NI] Summer indicator (1 if crash occurred during the summer, 0 otherwise) | - | - | –0.539 | –2.47 | - | - |
| [MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise) | - | - | - | - | 0.442 | 2.01 |
| **Vehicle characteristics** | | | | | | |
| [NI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | 0.309 | 2.21 | - | - | 0.490 | 2.79 |
| [MI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise) | –0.406 | –2.46 | - | - | - | - |
| [NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise) | 0.346 | 2.64 | - | - | - | - |
| [NI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise) | - | - | –1.927 | –3.12 | - | - |
| **Roadway characteristics** | | | | | | |
| [MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | 0.445 | 2.69 | - | - | - | - |
| [SI] Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise) | - | - | - | - | 0.976 | 1.98 |
| [NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise) | 0.296 | 2.19 | 0.372 | 2.18 | - | - |
| [MI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise) | 1.088 | 1.90 | - | - | - | - |
| **Environment characteristics** | | | | | | |
| [NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise) | - | - | 0.393 | 2.39 | - | - |
| **Model statistics** | | | | | | |
| Number of observations (*N*) | 3827 | | 2061 | | 3211 | |
| Number of estimated parameters (*K*) | 21 | | 17 | | 20 | |
| Log-likelihood at zero, $LL(0)$ | –4204.389 | | –2264.240 | | –3527.644 | |
| Log-likelihood at convergence, $LL(\beta)$ | –1497.669 | | –869.450 | | –1358.826 | |
| $\rho^2 = 1 - LL(\beta)/LL(0)$ | 0.644 | | 0.616 | | 0.615 | |
| Akaike information criterion (AIC) | 3037.3 | | 1772.9 | | 2757.7 | |
| Bayesian Information Criterion (BIC) | 3168.6 | | 1868.6 | | 2879.1 | |

**Table 13.** The marginal effects of contributing factors in different impact location models.

| Variable | Center | | | Left | | | Right | | |
|---|---|---|---|---|---|---|---|---|---|
| | NI | MI | SI | NI | MI | SI | NI | MI | SI |
| **2015** | | | | | | | | | |
| **Crash characteristics** | | | | | | | | | |
| [NI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | –0.1276 | 0.1130 | 0.0146 | –0.2021 | 0.1885 | 0.0136 | - | - | - |
| [NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | - | - | - | –0.0182 | 0.0169 | 0.0013 | - | - | - |
| [NI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | - | - | - | - | - | - | 0.0036 | –0.0034 | –0.0002 |
| [MI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | 0.0052 | –0.0052 | 0.0000 | - | - | - | - | - | - |
| [MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise) | –0.0219 | 0.0227 | –0.0008 | 0.0159 | –0.0159 | 0.0000 | –0.0110 | 0.0111 | –0.0001 |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | - | - | - | - | - | - | –0.0951 | 0.0886 | 0.0065 |
| [MI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | –0.1198 | 0.1227 | –0.0029 | - | - | - | - | - | - |
| [SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | - | - | - | –0.0329 | –0.0099 | 0.0428 | - | - | - |
| **Driver characteristics** | | | | | | | | | |
| [NI] Old driver indicator (1 if driver age over 50, 0 otherwise) | –0.0216 | 0.0178 | 0.0038 | - | - | - | - | - | - |
| [MI] Old driver indicator (1 if driver age over 50, 0 otherwise) | 0.0112 | –0.0118 | 0.0006 | - | - | - | - | - | - |
| [SI] Old driver indicator (1 if driver age over 50, 0 otherwise) | - | - | - | –0.0221 | –0.0006 | 0.0270 | - | - | - |
| [NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | 0.1744 | –0.1576 | –0.0168 | - | - | - | - | - | - |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | –0.0702 | 0.0717 | –0.0015 | 0.0872 | –0.0888 | 0.0016 | 0.0522 | –0.0534 | 0.0012 |
| [NI] Gender indicator (1 if driver was female, 0 otherwise) | –0.0408 | 0.0358 | 0.0050 | - | - | - | - | - | - |
| [MI] Gender indicator (1 if driver was female, 0 otherwise) | - | - | - | –0.0349 | 0.0356 | –0.0007 | –0.0327 | 0.0333 | –0.0006 |
| [NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | –0.0164 | 0.0128 | 0.0036 | - | - | - | –0.0077 | 0.0071 | 0.0006 |
| [MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | - | - | - | –0.0076 | 0.0080 | –0.0004 | - | - | - |
| **Temporal characteristics** | | | | | | | | | |
| [MI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise) | - | - | - | - | - | - | 0.0067 | –0.0069 | 0.0002 |
| [NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | –0.0055 | 0.0047 | 0.0008 | - | - | - | –0.0066 | 0.0061 | 0.0005 |
| [MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | - | - | - | –0.0078 | 0.0080 | –0.0002 | - | - | - |
| [MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise) | –0.0049 | 0.0051 | –0.0002 | –0.0049 | 0.0050 | –0.0001 | - | - | - |
| [MI] Autumn indicator (1 if crash occurred during the autumn, 0 otherwise) | - | - | - | 0.0001 | 0.0056 | –0.0057 | - | - | - |
| **Vehicle characteristics** | | | | | | | | | |
| [MI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise) | - | - | - | 0.0235 | –0.0240 | 0.0005 | - | - | - |
| [NI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | - | - | - | - | - | - | 0.0221 | –0.0208 | –0.0013 |
| [SI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | 0.0065 | 0.0016 | –0.0081 | 0.0032 | 0.0012 | -0.0044 | - | - | - |
| [MI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise) | - | - | - | - | - | - | 0.0057 | –0.0059 | 0.0002 |
| [NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise) | - | - | - | - | - | - | 0.0094 | –0.0089 | –0.0005 |
| **Roadway characteristics** | | | | | | | | | |
| [MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | - | - | - | - | - | - | –0.0330 | 0.0337 | –0.0007 |
| [MI] The number of lanes indicator (1 if the number of lanes is 4–6, 0 otherwise) | - | - | - | –0.0160 | 0.0163 | –0.0003 | - | - | - |
| [MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | –0.0089 | 0.0092 | –0.0003 | - | - | - | - | - | - |
| [NI] Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise) | –0.0228 | 0.0199 | 0.0029 | - | - | - | - | - | - |
| [MI] Speed limit 30-60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise) | - | - | - | –0.0326 | 0.0333 | –0.0007 | - | - | - |
| [NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise) | - | - | - | - | - | - | 0.0076 | –0.0071 | –0.0005 |

| Variable | Center | | | Left | | | Right | | |
|---|---|---|---|---|---|---|---|---|---|
| | NI | MI | SI | NI | MI | SI | NI | MI | SI |
| [NI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise) | - | - | - | - | - | - | 0.0050 | –0.0049 | –0.0001 |
| [MI] Intersection indicator (1 if crash occurred on the intersection, 0 otherwise) | - | - | - | - | - | - | –0.0165 | 0.0171 | –0.0007 |
| **Environment characteristics** | | | | | | | | | |
| [MI] Dark-unlighted indicator (1 if lighting condition is dark-unlighted, 0 otherwise) | - | - | - | 0.0068 | –0.0069 | 0.0001 | - | - | - |
| **2016** | | | | | | | | | |
| **Crash characteristics** | | | | | | | | | |
| [NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | –0.0032 | 0.0030 | 0.0002 | - | - | - | –0.0047 | 0.0040 | 0.0007 |
| [NI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | 0.0083 | –0.0077 | –0.0005 | 0.0069 | –0.0066 | –0.0003 | 0.0045 | –0.0043 | –0.0002 |
| [MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise) | –0.0222 | 0.0225 | –0.0003 | –0.0207 | 0.0210 | –0.0002 | - | - | - |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | –0.1977 | 0.1846 | 0.0131 | –0.0962 | 0.0903 | 0.0059 | –0.0888 | 0.0772 | 0.0116 |
| [NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise) | –0.0283 | 0.0265 | 0.0018 | - | - | - | - | - | - |
| **Driver characteristics** | | | | | | | | | |
| [NI] Old driver indicator (1 if driver age over 50, 0 otherwise) | –0.0287 | 0.0258 | 0.0029 | –0.0082 | 0.0078 | 0.0004 | - | - | - |
| [MI] Old driver indicator (1 if driver age over 50, 0 otherwise) | 0.0167 | –0.0180 | 0.0013 | - | - | - | –0.0074 | 0.0076 | –0.0002 |
| [NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | 0.3257 | –0.3103 | –0.0155 | 0.2242 | –0.2142 | –0.0100 | 0.1487 | –0.1334 | –0.0153 |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | –0.1898 | 0.1941 | –0.0043 | –0.1650 | 0.1716 | –0.0066 | - | - | - |
| [NI] Gender indicator (1 if driver was female, 0 otherwise) | –0.0318 | 0.0302 | 0.0016 | –0.0370 | 0.0350 | 0.0020 | –0.0220 | 0.0198 | 0.0022 |
| [NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | –0.0113 | 0.0105 | 0.0008 | –0.0118 | 0.0092 | 0.0026 | –0.0049 | 0.0041 | 0.0008 |
| [MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | - | - | - | 0.0052 | –0.0069 | 0.0017 | - | - | - |
| **Temporal characteristics** | | | | | | | | | |
| [SI] Weekday indicator (1 if crash occurred during the weekday, 0 otherwise) | - | - | - | 0.0026 | 0.0024 | –0.0050 | - | - | - |
| [NI] Afternoon indicator (1 if time of day is between 12 PM to 6:59 PM, 0 otherwise) | - | - | - | –0.0131 | 0.0124 | 0.0007 | - | - | - |
| [NI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | - | - | - | - | - | - | –0.0114 | 0.0098 | 0.0016 |
| [NI] Summer indicator (1 if crash occurred during the summer, 0 otherwise) | - | - | - | - | - | - | –0.0078 | 0.0069 | 0.0009 |
| **Vehicle characteristics** | | | | | | | | | |
| [SI] Passenger car involvement indicator (1 if passenger car being involved in the crash, 0 otherwise) | 0.0024 | 0.0019 | –0.0043 | - | - | - | - | - | - |
| [NI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | 0.0471 | –0.0444 | –0.0027 | 0.0571 | –0.0540 | –0.0031 | - | - | - |
| [NI] Vehicle age indicator (1 if the vehicle age is between 5 and 10 years, 0 otherwise) | –0.0086 | 0.0081 | 0.0005 | - | - | - | - | - | - |
| [NI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise) | - | - | - | - | - | - | –0.0887 | 0.0696 | 0.0191 |
| [MI] Vehicle age indicator (1 if the vehicle age is older than 10 years, 0 otherwise) | - | - | - | - | - | - | 0.0397 | –0.0428 | 0.0031 |
| **Roadway characteristics** | | | | | | | | | |
| [NI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise) | 0.0606 | –0.0584 | –0.0022 | - | - | - | - | - | - |
| [MI] Freeway indicator (1 if crash occurred on the freeway, 0 otherwise) | –0.0451 | 0.0460 | –0.0009 | - | - | - | - | - | - |
| [NI] Municipal street indicator (1 if crash occurred on the municipal street, 0 otherwise) | - | - | - | 0.0119 | –0.0110 | –0.0008 | 0.0114 | –0.0101 | –0.0013 |
| **Environment characteristics** | | | | | | | | | |
| [NI] Adverse weather condition indicator (1 if weather condition is adverse, 0 otherwise) | 0.0206 | –0.0193 | –0.0012 | 0.0355 | –0.0334 | –0.0021 | 0.0243 | –0.0216 | –0.0027 |
| **2017** | | | | | | | | | |
| **Crash characteristics** | | | | | | | | | |
| [MI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | - | - | - | –0.1383 | 0.1446 | –0.0063 | –0.1422 | 0.1452 | –0.0030 |
| [SI] Collision with fixed object indicator (1 if collided with roadside fixed object as the first harmful event, 0 otherwise) | - | - | - | –0.0237 | –0.0075 | 0.0312 | - | - | - |

| Variable | Center | | | Left | | | Right | | |
|---|---|---|---|---|---|---|---|---|---|
| | NI | MI | SI | NI | MI | SI | NI | MI | SI |
| [NI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | - | - | - | –0.0115 | 0.0103 | 0.0012 | - | - | - |
| [MI] Non-Collision indicator (1 if first harmful event was identified as non-colliding object such as a rollover, etc., 0 otherwise) | - | - | - | - | - | - | –0.0103 | 0.0105 | –0.0002 |
| [NI] Animal indicator (1 if animal involved in the crash, 0 otherwise) | 0.0113 | –0.0106 | –0.0007 | - | - | - | - | - | - |
| [NI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise) | 0.0149 | –0.0148 | –0.0001 | - | - | - | - | - | - |
| [MI] Non-functional damage indicator (1 if damage to vehicle is non-functional, 0 otherwise) | - | - | - | - | - | - | 0.0154 | –0.0154 | 0.0001 |
| [MI] Functional damage indicator (1 if damage to vehicle is functional, 0 otherwise) | 0.0207 | –0.0208 | 0.0001 | –0.0260 | 0.0262 | –0.0002 | 0.0219 | –0.0221 | 0.0002 |
| [NI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | - | - | - | –0.1938 | 0.1655 | 0.0283 | - | - | - |
| [SI] Disabling damage indicator (1 if damage to vehicle is disabling, 0 otherwise) | –0.0318 | –0.0124 | 0.0442 | - | - | - | –0.0075 | –0.0019 | 0.0094 |
| [NI] Straight driving indicator (1 if the vehicle was going straight preceding the crash, 0 otherwise) | - | - | - | –0.0199 | 0.0174 | 0.0025 | - | - | - |
| **Driver characteristics** | | | | | | | | | |
| [NI] Young driver indicator (1 if driver age below 30 years, 0 otherwise) | - | - | - | 0.0174 | –0.0154 | –0.0020 | - | - | - |
| [NI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise) | - | - | - | - | - | - | 0.0308 | –0.0293 | –0.0015 |
| [MI] Middle-aged driver indicator (1 if driver age between 30–50 years, 0 otherwise) | –0.0083 | 0.0086 | –0.0003 | - | - | - | - | - | - |
| [NI] Old driver indicator (1 if driver age over 50, 0 otherwise) | –0.0237 | 0.0193 | 0.0044 | –0.0114 | 0.0093 | 0.0021 | –0.0086 | 0.0073 | 0.0013 |
| [MI] Old driver indicator (1 if driver age over 50, 0 otherwise) | 0.0137 | –0.0149 | 0.0012 | 0.0114 | –0.0122 | 0.0008 | - | - | - |
| [NI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | 0.1564 | –0.1413 | –0.0151 | - | - | - | - | - | - |
| [MI] Safety restraint usage indicator (1 if driver used shoulder and lap belt, 0 otherwise) | –0.0631 | 0.0651 | –0.0020 | - | - | - | 0.0115 | –0.0124 | 0.0009 |
| [MI] Gender indicator (1 if driver was female, 0 otherwise) | –0.0318 | 0.0284 | 0.0034 | –0.0438 | 0.0452 | –0.0013 | –0.0327 | 0.0334 | –0.0007 |
| [NI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | –0.0188 | 0.0151 | 0.0037 | - | - | - | –0.0228 | 0.0187 | 0.0041 |
| [MI] Physically impaired driver indicator (1 driver is impaired by alcohol, drugs, illness, or fatigue, etc., 0 otherwise) | - | - | - | –0.0061 | 0.0065 | –0.0004 | 0.0120 | –0.0129 | 0.0009 |
| **Temporal characteristics** | | | | | | | | | |
| [SI] Early morning indicator (1 if time of day is between 12 AM to 5:59 AM, 0 otherwise) | - | - | - | - | - | - | 0.0008 | 0.0002 | –0.0010 |
| [MI] Spring indicator (1 if crash occurred during the spring, 0 otherwise) | - | - | - | - | - | - | –0.0089 | 0.0091 | –0.0002 |
| [MI] Summer indicator (1 if crash occurred during the summer, 0 otherwise) | - | - | - | - | - | - | –0.0055 | 0.0057 | –0.0001 |
| **Vehicle characteristics** | | | | | | | | | |
| [NI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | 0.0768 | –0.0696 | –0.0072 | 0.1030 | –0.0923 | –0.0107 | 0.0323 | –0.0294 | –0.0029 |
| [MI] Insurance indicator (1 if vehicle was insured, 0 otherwise) | - | - | - | –0.0488 | 0.0501 | –0.0013 | - | - | - |
| [SI] Vehicle age indicator (1 if the vehicle age is less than 5 years, 0 otherwise) | –0.0023 | –0.0008 | 0.0032 | - | - | - | - | - | - |
| **Roadway characteristics** | | | | | | | | | |
| [NI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | –0.0963 | 0.1088 | -0.0125 | - | - | - | - | - | - |
| [MI] Traffic controls indicator (1 if traffic control functioned, 0 otherwise) | 0.0482 | –0.0432 | -0.0050 | - | - | - | - | - | - |
| [SI] The number of lanes indicator (1 if the number of lanes is 1–3, 0 otherwise) | –0.0055 | –0.0021 | 0.0076 | –0.0078 | –0.0024 | 0.0102 | - | - | - |
| [NI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | - | - | - | –0.0109 | 0.0088 | 0.0021 | - | - | - |
| [MI] The number of lanes indicator (1 if the number of lanes is greater than 6, 0 otherwise) | - | - | - | 0.0096 | –0.0103 | 0.0007 | - | - | - |
| [SI] Speed limit 30–60 mph indicator (1 if speed limit is between 30 and 60 mph, 0 otherwise) | - | - | - | - | - | - | –0.0070 | –0.0014 | 0.0084 |

## 7. Conclusions

Using a three-year single-vehicle crash dataset under adverse road surface conditions in Ohio from 2015 to 2017, this study investigated the heterogeneous impacts, temporal instability, and non-transferability of various determinants on driver injury severities across different vehicle impact locations. Three groups of random parameters logit models with the heterogeneity in the means (and variances) corresponding to center, left-side, and right-side crashes were employed. A wide range of contributing factors was considered, including crash characteristics, driver characteristics, temporal characteristics, vehicle characteristics, roadway characteristics, and environment characteristics. Three crash injury severity categories were determined as discrete outcome variables: no injury, minor injury, and severe injury. The results of likelihood ratio tests indicated an overall temporal instability and locational non-transferability while some indicators, such as hitting animals, old drivers, safety restraint usage, female drivers, physically impaired drivers, and vehicles with insurance, were observed to be of temporal stability and impact location transferability. This study also examined the impact of year-to-year and location-to-location shifts by comparing the probability differences between out-of-sample predictions and within-sample observations. The results showed varying magnitudes and inconsistent directions of distribution characteristics, including mean, skewness, kurtosis, and prediction accuracy, across different locations and periods. Furthermore, this study suggested that the net effects of aggregate location-to-location shifts were greater than the net effects of year-to-year shifts. Consequently, the non-transferability of impact location had a higher influence on the prediction accuracy than the temporal instability. This highlights the importance of appropriately addressing the temporal instability and impact location variations in crash prediction.

Based on the locational variation and temporal instability of contributing factors on driver injury severities in adverse-road-involved crashes, a series of proactive countermeasures could be formulated to effectively prevent and mitigate crashes associated with adverse road conditions. Regarding the non-transferability of impact locations, the current study reveals that dark-unlighted conditions pose a higher risk of severe injuries for left-side crashes instead of its center and right-side counterparts on adverse road surfaces. As a result, installing additional lighting on the left side of roads is recommended. Furthermore, the implementation of advanced warning systems, such as variable message signs, can effectively notify drivers of potential hazards on the left front side, especially in areas with limited lighting conditions. Concerning the movement type preceding crashes, the finding deserves considerable attention that probabilities of severe injuries increase for center and left-side collisions even when the vehicle is driving straight on adverse road surfaces. This suggests that targeted education programs should be implemented to enhance drivers' safety awareness and remind them to avoid dangerous driving behaviors, such as aggressive driving, improper turns, and speeding. Considering the direct lateral force sustained by drivers and the associated high possibility of fatal injuries in left-side crashes, protective measures such as side airbags and active damping systems could be equipped on vehicles to mitigate the severity of driver injury, along with infrastructure improvements like the installation of crash barriers on the left side of roads. Additionally, the early morning indicator is found to be more likely to result in severe injuries in right-side crashes. Therefore, it is recommended to utilize technology channels to provide time-specific dynamic information reminders to drivers. This can involve utilizing broadcast media to deliver real-time updates on road conditions and driving tips to drivers, enabling them to take more appropriate precautions to reduce the likelihood of severe injuries in the early morning. In terms of the insights obtained from temporal instability, taking the vehicle aged 0–5 years as an example, it is observed to be associated with smaller probabilities of severe injuries in 2015, whereas showing greater effects in 2017. This result underscores the importance of advancing autonomous driving technologies to mitigate the heterogeneous impact of brand-new automobiles on drivers' adaptation to new features.

This research emphasizes the necessity of considering unobserved heterogeneity, temporal instability, and impact location non-transferability in determining the driver injury severity of adverse-road-involved single-vehicle crashes at a disaggregate level. Despite these attempts, there might be some limitations in the current study. This paper only explores the impact location non-transferability with the Ohio cases in center, left-side, and right-side crash datasets. More detailed location divisions, multiple impact directions, and more regions could be considered to further explore the locational non-transferability and spatial instability under adverse road surface conditions in the future. In addition, the self-selectivity problem associated with non-random samples may exist in the current study (Mannering et al., 2020), i.e., less safe drivers may be over-represented in the accident data since safer drivers may avoid driving under adverse road surface conditions considering the substantial increase in risks. It should also be noted that severe injury crashes are a minority in the Ohio crash dataset and the imbalanced dataset could potentially introduce bias in parameter estimation and result in inaccurate inferences (Gao et al., 2021; Mannering and Bhat, 2014). In the future, sampling techniques such as under-sampling or over-sampling methods can be employed to balance the number of samples across different categories (Yuan et al., 2022). Additionally, combining the finite element analysis software and crash test to load impact forces in different directions can also provide a supplementary way to comprehensively uncover the driver injury mechanism, which is beneficial to optimize the vehicle structure, promote the development of vehicle shock absorbers, and improve overall driver safety.

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